The Impact of the Financial Reforms Influenced by Religious Financial Principles on the Stock Market in the Kingdom of Saudi Arabia

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ABSTRACT

This thesis aims to understand the effect of the financial reforms introduced by the Capital Market Authority (CMA) in Saudi Arabia in 2015 on the performance of stock market segments based on Islamic financial principles (IFP). These financial reforms, which include attracting qualified foreign institutional investors (QFIIs) and the reclassification (upgrading) of the stock market's status to become an emerging market, aim to improve the capital market's regulatory framework and foster its growth. Based on this background, this study examines how stock market performance has been impacted by comparing market changes pre- and post-reform in terms of return, level of volatility, interdependence of the market with other markets (the spillover effect) and asset allocation decisions.

The study uses a time series of daily data for five Saudi stock indices, which are based on IFP, and three global markets (Brent, WTI and S&P 500) for a 12-year period that started on January 04, 2010. These indices include three pure Islamic stock indices (IS1, IS2 and IS3), a mixed stock index (MS), and a non-Islamic stock index (CS). For the purpose of analysis, collected data are divided into two subsamples to represent the pre- (2010–2015) and post-reform periods (2016–2021).

The analysis of descriptive statistics shows that all indices recorded a decline in average return and all other risk-adjusted return measures (i.e., the Sharpe ratio and Treynor ratio) in the post-reform period. However, the historical risk measures, such as standard deviation, skewness, value at risk and conditional value at risk, used signal an increase in overall risk level during the post-reform period. Reductions in returns and increases in risks could have been affected by correcting previously mispriced stocks as a consequence of strengthening market regulation (Singh & Roca 2021). To gain better

insight into the changes in the risk and return characteristics in the Saudi stock market, probable changes in the volatility patterns (leverage effect of daily Saudi stock returns and volatility persistence) have been examined using GARCH-family econometrics models. The findings of our econometric analysis indicate that bad news carries a larger and longer effect on market volatility in the post-reform period irrespective of the nature of the shares. This could be due to the integration of the Saudi stock market with global markets (Jayasuriya 2005). The findings also show that conventional and mixed stock indices are more vulnerable to bad news than Islamic stock indices. This could be due to the differences in investment strategies (active or passive) used by investors who hold Islamic stocks and those who hold conventional (non-Islamic) stocks. Islamic stockholders seem to have passive strategies, which could lead to fewer stock transactions (Alam et al. 2017).

The volatility spillover across Saudi stock indices, three other global indices (two crude oil price indices (Brent and WTI) and one global stock index (S&P 500) has been examined to determine how global integration, which was one of the main aims of the financial reforms, has impacted the Saudi stock market. As the Saudi economy is heavily dependent on petroleum production and distribution, oil price movements are detrimental to all economic activities in the country. Therefore, an investigation of the impact of oil price movements on stock returns is important. Through econometric analysis conducted using ARMA-GARCH, CCF and VAR-GARCH-BEKK, the study determined the volatility interdependence between oil market indices, the US stock market, and the Saudi stock market. The findings indicate bidirectional volatility spillover between each pair of all indexes investigated during both periods, with spillover increasing in the post-reform period. This suggests that liberalising the Saudi stock market with Islamic stock indices has resulted in stronger interdependency with the oil market and US stock market compared to the non-Islamic stock index.

The findings are then used to obtain the implications on the portfolio management such as optimal portfolio weights and hedge ratios for asset allocation decisions. The findings encourage the allocation of more capital to Saudi stock indices rather than oil and the allocation of a lower proportion of Saudi stocks in a Saudi/S&P 500 portfolio for risk-averse investors during all periods. It also suggests reducing oil weight and increasing S&P 500 weight when reconstructing a portfolio with Saudi stocks in the post-reform period.

The findings of this study have important implications for portfolio construction, suggesting the need to consider the IFP. Moreover, these findings indicate that advancing the liberalisation of the Saudi market can have significant benefits. Not only is this expected to bolster the local economy in alignment with Saudi Vision 2030, but it also holds potential for contributing to the achievement of the United Nations' sustainable development goals. Finally, this research discusses further implications for policy and highlights the need for future investigations in this area.

DECLARATION

"I, Abdullah Alsalloum, declare that the PhD thesis entitled "The Impact of the Financial Reforms Influenced by Religious Financial Principles on the Stock Market in the Kingdom of Saudi Arabia" is no more than 80,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work".

"I have conducted my research in alignment with the Australian Code for the Responsible Conduct of Research and Victoria University's Higher Degree by Research Policy and Procedures".

Signature	**Date**
Abdullah Alsalloum	14/02/2023

DEDICATION

I dedicate this work to my beloved ones, who have always been a source of support, encouragement, wisdom and love.

I am forever grateful for your prayers.

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This journey has not only been a wonderful opportunity to meet and learn from great examples, but it has also been a chance to learn from and overcome my mistakes. For that, I am truly thankful.

LIST OF PUBLICATIONS AND AWARDS FROM THIS THESIS

Refereed Conference Participation

The 2019 Victoria University Business School HDR Student Conference, Victoria University, 26th November 2019.

Awards received for work based on this thesis

The 2019 Victoria University Business School HDR Student Conference Award for the best presentation for the finance stream, Victoria University, Melbourne, 26th November 2019.

LIST OF ABBREVIATIONS

Words	Abbreviation
ARCH	Autoregressive Conditional Heteroscedasticity
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GCC	Gulf Cooperation Council
KSA	Kingdom of Saudi Arabia
IFP	Islamic Financial Principles
MENA	Middle East and North Africa region
PP	Phillips Perron
OLS	Ordinary Least Square
OPEC	Organization of the Petroleum Exporting Countries
AIC	Akaike information criterion
SIC	Schwarz’s Bayesian information criteria
HQC	Hannan-Quinn information criteria
TASI	Tadawul All Share Index
EGARCH	Exponential Generalized Auto Regressive Conditional Heteroskedasticity
GJR-	Glosten Jagannathan and Runkle
KPSS	Kwiatkowski, Phillips, Schmidt and Shin unit root test
US	United States
EU	European Union
BT	Bloomberg Terminal - Data Base
WTI	West Taxes Intermediate crude oil
Brent	Brent Crude oil
S&P500	Standard and Poor’s 500 index

VAR	Vector Auto Regression
SAMA	Saudi Arabian Central Bank
MGARCH	Multivariate Generalised Autoregressive Conditional Heteroscedasticity
BGARCH	Bivariate Generalised Autoregressive Conditional Heteroscedasticity
BHHH	Berndt, Hall, Hall, and Hausman
BEKK	Baba, Engle, Kraft and Kroner
IS1	Islamic Stock Index 1
IS2	Islamic Stock Index 2
IS3	Islamic Stock Index 3
MS	Mixed Stock Index
CS	Conventional Index
QFIIs	Qualified Foreign Institutional Investors

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CHAPTER 1: INTRODUCTION

1.1 Background and Motivation

1.1.1 Introduction

Saudi Arabia introduced a financial reforms program (further liberalising) to attract more foreign institutional investors to its stock market in 2015. It was believed that foreign institutional investors would contribute to achieving the goal of formulating an advanced stock market (Tadawul 2015). To this end, the Capital Market Authority (CMA) launched the Qualified Foreign Institutional Investors Program (QFII) in 2015. In September 2016, CMA increased the foreign institutional investors' ownership limit on holding shares of listed firms from 25% to 49% (Tadawul 2018). In 2018, Tadawul, the Saudi stock market, made the necessary arrangements to integrate with three of the leading global indices for emerging markets: FTSE Russell, MSCI and S&P.

These factors reinforce each other to develop the Saudi stock market. Investing in stock market modernising reforms can drive an improvement in operational market efficiency. In other words, the CMA in Saudi Arabia aligns the operational regulations in its stock market to international standards to reduce the transaction time and cost with the expectation to attract global institutional investors, thus increasing the liquidity and size of the stock market and implying a better market status, which can improve the status of the Saudi stock market in global indices to attract additional investments (Tadawul 2015).

However, the liberalisation reforms may encounter some local obstacles. The society could have different expectations based on the religious principles embodied in Islamic ideologies. These religious principles could constrain certain activities. In Saudi Arabia, decision-making behaviours of individuals have been dictated by religious principles. For instance, religious principles may identify some investment decisions as acceptable and some as not acceptable. These beliefs may influence investment decisions related to the stocks listed in the Saudi market (Liu et al. 2014). On the other hand, foreign investors may not be dictated by Islamic principles. Therefore, they may have the desire to invest in both the accepted and non-accepted stocks or investments based on Islamic fundamentals. Consequently, restricting investment opportunities based on the Islamic religion may undermine the full potential of stock market development (Alawadhi & Dempsey 2017). To illustrate, Islamic fundamentals allow investing in any stock in general but prohibit some industries that are incompatible with Islamic regulations (e.g. alcohol and non-halal meat) as well as businesses that have ‘Riba’ (interest), ‘Gharar’ (uncertainty) and ‘Maysir’ (gambling) (Iqbal & Mirakhor 2012).

As a direct outcome of a practice of these Islamic fundamentals, stock markets in Islamic societies classify stocks into three categories: Pure-Islamic, Mixed-Islamic and Non-Islamic. Accordingly, this classification has provided a clear identification for potential investors for the selection of the most suitable investment based on their expectations. Hence, the understanding of the impact of religious principles on Islamic society is essential in any attempt to develop a stock market. Therefore, further investigation is important to determine how liberalisation reform announcements interact with the performance of these three classes of stocks created based on Islamic religious principles.

An empirical analysis was performed to investigate how the announcements of stock market liberalisation reforms and decisions to integrate with the global emerging stock market indices influenced the three Saudi stock categories. To accomplish this goal, it is important to consider that the Saudi stock market (including the three Saudi stock categories classified based on Islamic principles) is linked to international financial markets through the channels of trade of goods and services, political ties and financial integration. This enables the possibility of a global market volatility spillover into the local economy and stock market.

Furthermore, the implemented reforms allow for an increase in foreign direct investments and for integrating the Saudi stock market into global indices. The volatility spillover can take the shape of a transfer of risk from global hubs, such as the oil market and the US stock market, to the local Saudi market. It is possible that shocks to the global indices would also affect TASI and the three Saudi stock categories.

As a result, a volatility spillover investigation was conducted between different global markets and three classes of assists (classified based on religious financial principles) listed in the Saudi stock market. The first market to consider is the oil market. Oil prices are considered the key driver of the Saudi economy and stock market. Therefore, the volatility spillover in the oil market and the three different classes of stocks in the Tadawul before and after the announced reforms are examined to determine how they impact the overall Saudi stock market, including the three Saudi stock categories.

It is also rational to identify any change in the linkage between other global financial markets and the three Saudi stock categories before and after the liberalisation reform. The volatility spillover between other global financial markets, such as between the US stock market and the Saudi stock market (including the three Saudi stock categories), are also considered in this investigation because there is value in an empirical investigation into the impact of liberalisation reform announcements on the volatility spillover among the three stock categories, the oil market and the US stock market.

1.1.2 Problem Background

A well-developed capital market would facilitate an efficient distribution of scarce resources to different economic activities. Therefore, a developing capital market is an essential feature for emerging economies (Ngare et al. 2014). The capital markets include the stock market and allocate savings, facilitate investments and enhance capital productivity (Arshad et al. 2016). Therefore, authorities of capital markets are keen to develop their stock markets by implementing institutional reforms, such as increasing the level of liberalisation to attract more foreign investors (Kearney & Lucey 2004; Ahmed & Mmolainyane 2014). Consequently, foreign capital flows to the emerging capital market, which develops stock market performance by increasing market efficiency, decreases stock price volatility (Vo 2015; Chen et al. 2013) and increases asset returns (Al Nasser & Hajilee 2016; Balakrishnan et al. 2019); however, globalisation can also cause these markets to be more susceptible to global risk factors, which results in high sensitivity to global crises (Mollah & Mobarek 2016).

The liberalisation of the stock market could enhance stock market efficiency because the removal or reduction of restrictions on trade increases the available information in markets (Balakrishnan et al. 2019). Stock market liberalisation uses various events to attract foreign investors (Bekaert et al. 2011; Henry 2000). In this context, the Saudi stock market has applied reforms to implement liberalisation[1]. The stock market status reclassification is a significant event for global indices of emerging equity markets (FTSE Russell 2018). Although there are many academic studies on equity market liberalisation and international stock market integration, few have studied the consequences of the

[1] See table (4); the table illustrates the announcements schedule regarding the Saudi stock market.

reclassification of stock markets and the integration of global emerging markets indexes (Abuzayed & AlFayoumi 2017; Burnham et al. 2018; Mendes & Martins 2018).

Furthermore, there is a need for a further investigation of how the liberalisation attempts in Saudi Arabia's stock market would cope with the Islamic financial principles. This is important because the liberalisation strategy aims to reclassify stocks into three classes based on Islamic principles. Therefore, it is important to investigate how the reclassification based on social norms has supported the development of the stock market in Islamic countries (Alawadhi et al. 2016). There is evidence that shows that social norms—Islamic financial principles in particular—can create market segmentation issues. Participants in an Islamic society's stock market prefer to avoid buying financial assets that conflict with Islamic principles, which leads to an increased demand and liquidity for stocks conforming to Islamic principles for investment (Alawadhi & Dempsey 2017; and Alhomaidi et al. 2019). Therefore, one could argue that if global foreign investors do not necessarily share the same faith, beliefs and values as most local investors, the Islamic financial principles may create an issue when attempting to open the local stock market (Alawadhi & Dempsey 2017). Market segments that do not comply with religious beliefs may diminish the capacity to attract capital from Islamic investors, which would increase the costs of accessing capital and would increase liquidity risk (Alawadhi et al. 2016).

1.2 Research Aims and Questions

1.2.1 Study Aim

This research aims to explore the impact of modernisation (liberalisation) initiatives on the Saudi stock market (Tadawul) in line with Islamic financial principles. To help accomplishing this purpose, the study addresses the following objectives:

To examine the impact of Saudi stock market (liberalisation) reforms on the risk-adjusted performance of three groups of stocks segmented based on Islamic financial principles.

To analyse the volatility patterns for each of the three stock categories in Saudi Arabia before and after the market reforms.

To assess the volatility spillover between oil market and US stock market returns for each of the three Saudi stock categories before and after the reforms.

To investigate whether the selection of an optimal portfolio varies among the three stock categories based on Islamic financial principles before and after the financial reforms initiated in mid-2015.

1.2.2 Research Questions

The implementation of strategic reforms facilitates the future development of the Saudi stock market. These reforms adhere to international standards, follow the general global theme of capital market liberalisation and encourage participation in the leading global market indices to attract foreign investors and to increase capital flow. The following questions are addressed:

Whether the Saudi Stock market reforms have changed the performance of three stocks based on the Islamic principles?

Does Volatility pattern vary for each of the three stock categories in Saudi Arabia before and after the reforms?

Does the volatility spillover between (oil market/US Stock market) returns vary for each of the three Saudi stock indices categories before and after the reforms?

Does the selection of an optimal portfolio vary among the three stock categories based on Islamic principles before and after the financial reforms?

1.3 Study Scope and Conceptual Framework

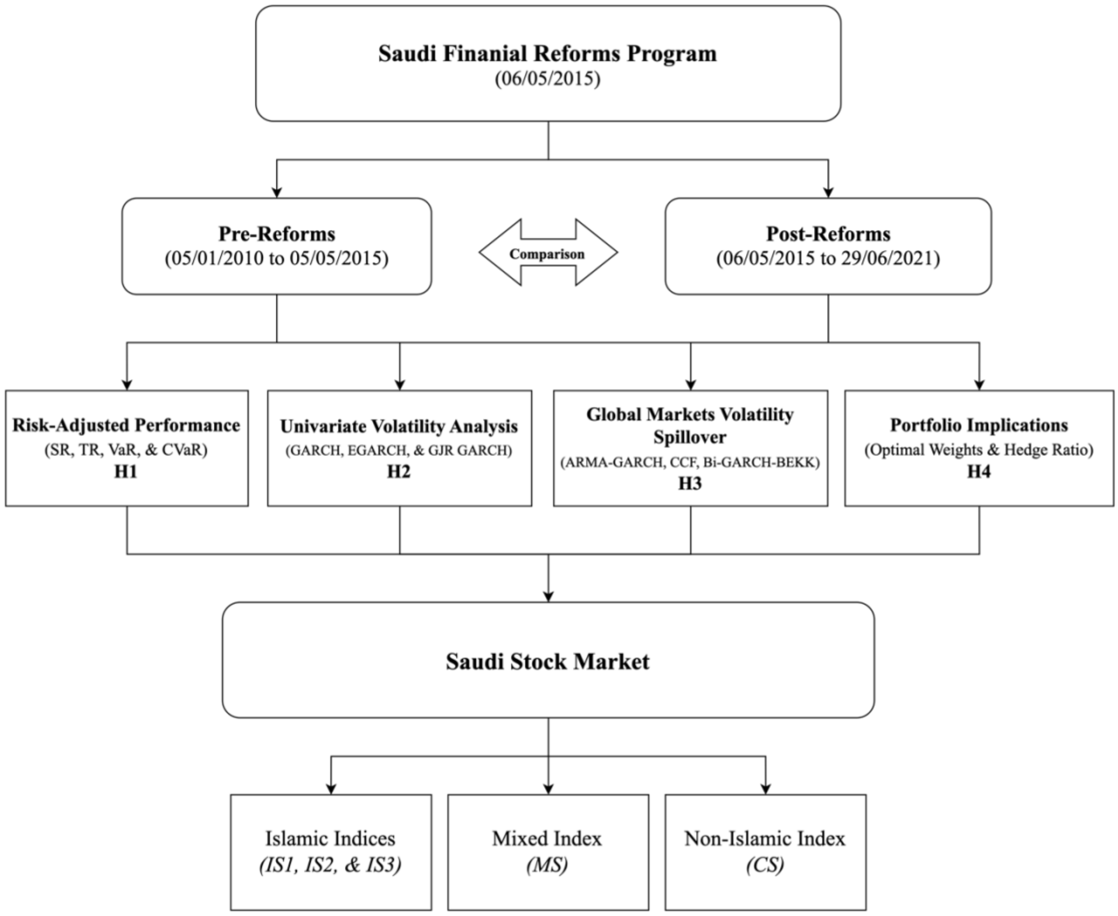
The conceptual model in Figure 1.1 illustrates the study framework. The choice of the Saudi Arabian market as the focus of this study is supported by several justifications. Firstly, Saudi Arabia holds significant importance as a member of the G20 and possesses the largest market in the MENA (Middle East and North Africa) region. By examining the Saudi Arabian market, we can gain insights into the dynamics and characteristics of a key regional economy.

Moreover, the Saudi Arabian market is heavily dependent on oil, making it particularly susceptible to fluctuations in energy prices. This dependency offers a unique opportunity to investigate the influence of oil price movements on the stock market and assess its potential impact on financial outcomes.

Furthermore, as a leading Islamic country, Saudi Arabia provides an interesting context to explore the influence of Islamic financial principles on the stock market. Additionally, with the recent economic liberalisation efforts as part of Vision 2030, the Saudi Arabian market has experienced increased openness to global economic engagement. This presents a compelling aspect to examine how the stock market is affected by these reforms and its integration with the global economy.

Regarding the selected time period of (2010-2021), it is justified by the availability of extensive data specially for Islamic stock market indices, which have been consistently recorded since 2010. This duration encompasses both pre- and post-liberalisation reforms, enabling a comprehensive analysis of the main objectives of this thesis. By studying this period, we can capture the effects of significant market developments and policy changes on the stock market.

Figure 1.1: Conceptual framework.



Note: This chart shows the relationship between the stock categories, the Saudi stock market and the factors that affect the risk-adjusted performance, volatility pattern, volatility spillover to the stock market.

1.4 Contribution to Knowledge and Statement of Significance

1.4.1 Contribution to Knowledge (Academic Contribution)

This research focused on the impact of religious principles on the existence, size and direction of volatility spillover for three different classes of stocks in Tadawul and global markets. The change in the volatility spillover in these three classes and in global markets was also measured in terms of stock market liberalisation policy and its practice implications. It contributes to current empirical knowledge in the stock market literature by examining one of the largest stock markets in the Middle East and North Africa (MENA). Moreover, this study adds to the understanding of how religious principles may influence the development of local stock markets in Islamic societies. To illustrate, the investigation measured return volatility spillover between three different classes of stocks classified by the Islamic fundamentals and external global markets, such as the oil market and the US stock market. Furthermore, this project is extended to include a portfolio weight investigation based on the outcomes of the volatility spillover test. Thus, the aim is to provide empirical evidence on the effects of religious financial principles on the stock market in terms of liberalisation reforms in MENA and other Islamic societies.

There are several studies on the effects of financial liberalisation on capital market performance, particularly those that examine the participation of foreign investors in stock markets (Henry 2000). To determine their exact contributions, the impacts of two fundamental reforms were investigated: 1) the establishment of the qualified foreign institutional investors program and 2) increasing foreign institutional investors' ownership limits. This investigation articulates the religious dimension of the liberalisation reforms in the largest capital market in MENA and Gulf Cooperation Council (GCC) countries.[2] To elaborate, this work builds on a large body of theoretical and empirical literature concerning religious principles and stock market development reforms and examines their implications for the dynamics of risk flow from global markets to a local stock market in an Islamic society.

How the classification of shares based on Islamic financial principles might affect stock market development is poorly understood. This study may be the first to investigate how

[2] The GCC is an alliance of six countries: Saudi Arabia, United Arab Emirates, Bahrain, Kuwait, Qatar and Oman.

upgrading the stock market status impacts the volatility spillover between a local stock market and global markets in an Islamic context.

This research also contributes to existing knowledge by providing empirical evidence of the Islamic categorical perspective in the stock market. Existing studies that have addressed religious beliefs have used strict Islamic screening categories in their analyses. Alawadhi and Dempsey (2017), for instance, examined stock market outcomes based on Islamic financial principles by dividing the stock market into two categories, Islamic and non-Islamic stocks, which they compared using indicators of liquidity and liquidity risk; however, this study examined how liberalisation and the reclassification of global indices interact with Islamic financial principles (in which the stock market is viewed as three classes of stock), which may lock in the full potential of these reforms. To elaborate, this proposal is different from Alawadhi and Dempsey's (2017) in that it considers different econometrics methodologies using time-series techniques to model the stocks' return and volatility figures instead of using cross-sectional analyses of liquidity.

1.4.2 Statement of Significance (Practical Contribution)

The impact of the QFII program and the reclassification of the stock market in Saudi Arabia has not been examined. The results of such an investigation would have some policy implications. This study identified the implications for capital market authorities, investors, global index providers and future researchers. The results of this research will help inform the Saudi CMA about the efficacy of liberalisation reforms in the stock market in formulating an advanced capital market. The outcomes of this study will also inform investors regarding how to minimise their risks by using portfolio diversification strategies. Furthermore, foreign investors will be able to understand how the classification of religious beliefs could affect their investment strategies in Islamic countries. It will also assist global index providers with reviewing, reclassifying and including a new stock market as well as giving them ideas about how they might improve their procedures. As a pioneering study, this project will assist future researchers by investigating the impact of foreign capital inflows on the stock market in the context of MENA and other Islamic countries.

1.5 Structure of the Thesis

As shown in Figure 1.2, this thesis is comprised of seven chapters as follows:

The first chapter presents the introduction, a summary of previous studies, the significance of the research, its aims, the research questions, the research contribution and the structure of the thesis.

The second chapter presents an overview of Saudi Arabia in general, its economy and Saudi stock market information to provide the elements that are necessary for readers to understand the study methodology, results and discussion.

The third chapter includes a review on relative theoretical and empirical literature to the research topic, 'The Impact of the Financial Reforms Influenced by Religious Financial Principles on the Stock Market in the Kingdom of Saudi Arabia'.

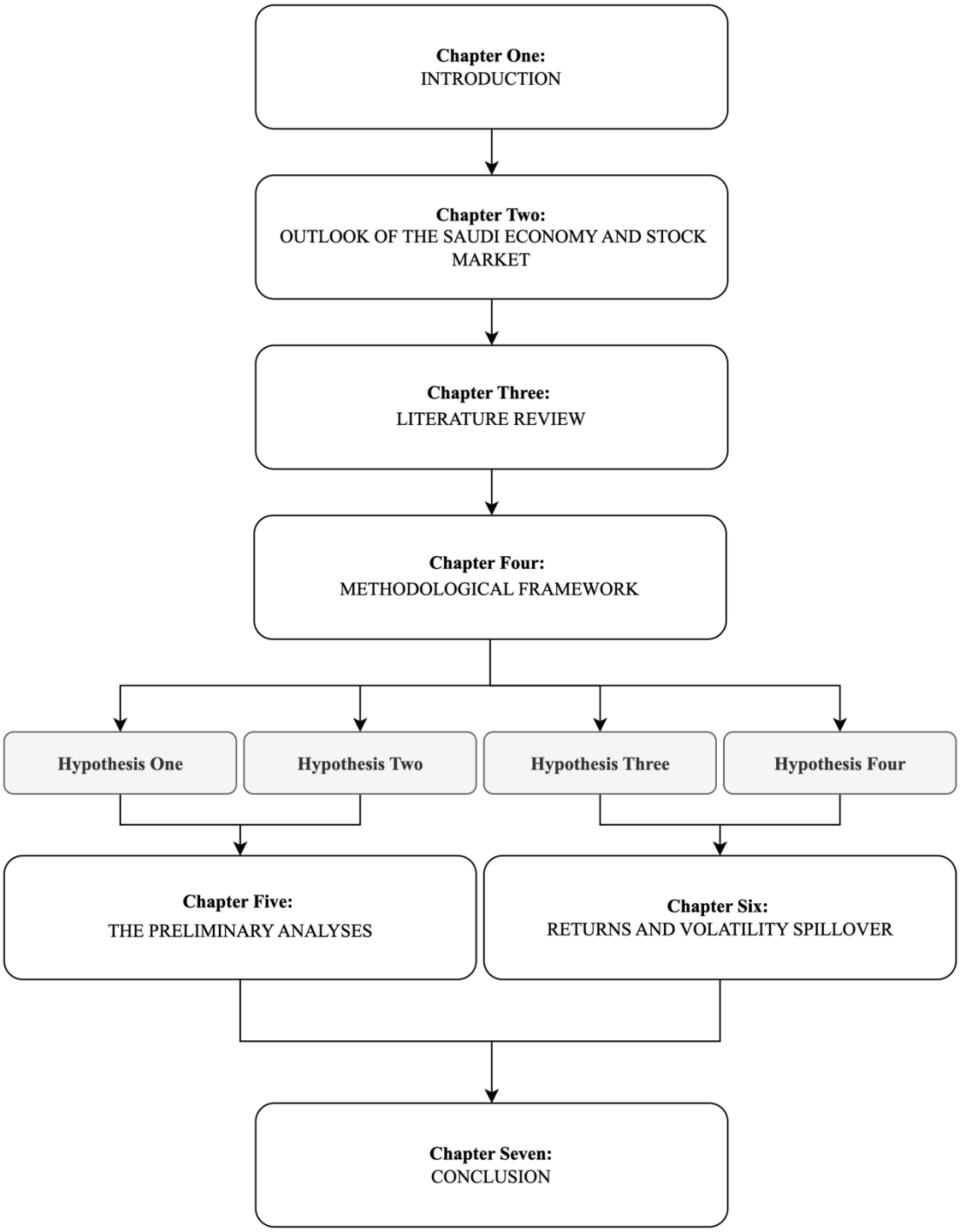
Chapter Four presents the data and variables required to achieve the research objectives and to answer the research questions. Basically, it describes the developed methodology used to model the return volatility and to measure the impact of the financial reforms and religious financial principles on the volatility spillover in the Saudi stock market.

Chapter Five presents the results of the preliminary analysis, including descriptive analyses, diagnosing stationarity of data sets, multicollinearity across markets, granger causality, and ARCH-LM test. Also, the chapter presents the impact of the global markets on the risk-adjusted performance of the Saudi stock indices. Finally, the findings of the volatility analysis based on the univariate GARCH models including volatility persistence and half-life is presented.

Chapter Six provides the results and discussion of the volatility spillover investigation including three different statistical techniques (ARMA-GARCH, CCF, and Bi-GARCH-BEKK), as well as its implications on the optimal portfolio.

Finally, **Chapter Seven** concludes the discussions of this thesis and the policy implications of the research, its limitations and future research recommendations.

Figure 1.2: Thesis structure in relation to research hypotheses



1.6 Summary

This chapter introduces the current thesis by providing a comprehensive background of the study and a brief historical overview of the research's context, the research topic, and the reasons for the research. Additionally, the chapter outlines the motives, aims, questions, and implications of the study on a theoretical, academic, and practical level. It also illustrates the conceptual framework which articulates the components of the study and simplifies its purpose. Furthermore, this chapter outlines the structure and origination of the thesis related to the aims of the study. This provides a clear understanding of the purpose and implications of the thesis, as well as its impact on the relevant fields of study.

CHAPTER 2: OUTLOOK OF THE SAUDI ECONOMY AND STOCK MARKET

2.1 Introduction

This chapter offers an overview of Saudi Arabia by providing a description of its country, economy, and stock market. It starts with a brief general history of the country before going into an analysis of the state of the economy and its financial markets. The chapter then examines the historical development of the financial markets in Saudi Arabia, highlighting key statistics and reforms, such as the Qualified Foreign Institutional Investors (QFIIs) Program and the stock market reclassification program.

2.2 General Information

The Kingdom of Saudi Arabia (KSA) is a monarchy with a constitution based on Sharia (Islamic) law, which articulates the government's and people's rights and responsibilities. As shown in Figure 2.1, KSA is located in the Arabian Peninsula with a land area of 2,150,000 km^2 (830,000 square miles). According to the Saudi General Authority for Statistics in (2021), the total population of Saudi Arabia is 31,742,308 people, of which approximately 70% are Saudi nationals. The King of Saudi Arabia is called the Custodian of the Two Holy Mosques, which refer to the cities of Makkah and Madina. Even though the current kingdom was officially founded on September 23, 1932, the First Saudi State was founded on February 22, 1727. This is why February 22 has been designated as the founding day, while September 23 is celebrated as the national day of Saudi Arabia. The formal language spoken by Saudis is Arabic, but English is widely spoken throughout the country. The official currency in the kingdom is called the Saudi Arabian Riyal (SAR).

In Saudi Arabia, the government and people use the Hijri calendar as the official date format, which works alongside the Gregorian calendar.

Figure 2.1: World Map and Saudi Arabia Location

Source: elaborated by the researcher

This study seeks to shed light on the particularities of the Saudi Arabian economy and its stock market, which differs from other markets. Examining this subject requires an in-depth look at the factors that set the Saudi Arabian economy apart, such as its geopolitical landscape, economic policies, and financial regulations. By exploring these aspects in detail, researchers can gain a better appreciation of the significance of this topic and why it is worth investigating.

2.3 Overview of the Economy of Saudi Arabia

Saudi Arabia has joined many active financial organisations in the world as a member. For instance, In 1957, Saudi Arabia gain both memberships of the International Monetary Fund (IMF) and the World Bank (WB) (G20 2008). In addition to that, KSA is a founder and permanent member of the Organisation of Petroleum Exporting Countries (OPEC), which was established in 1960. It is also became a member of the Group of 20 (G20) since 1999, which is a group of the largest 19 economies and European nations with representatives of the WB and IMF (G20 2008). Moreover, Saudi Arabia has joined the World Trade Organisation (WTO) membership in 2005. Saudi Arabia became a participant in the Sustainable Stock Exchanges (SSE) initiative, established by the United Nations (UN) in late 2018. This initiative aims to promote the 2030 sustainable development goals of the UN. Additionally, KSA is considered as a leading and largest economy in the MENA region as well as Islamic and Arab world with GDP of USD1.0106 trillion in 2022. Furthermore, Saudi Arabia is a founding country and the largest economy of the Gulf Cooperation Council (GCC) which is established in 1981.

2.3.1 Economics of Saudi Arabia

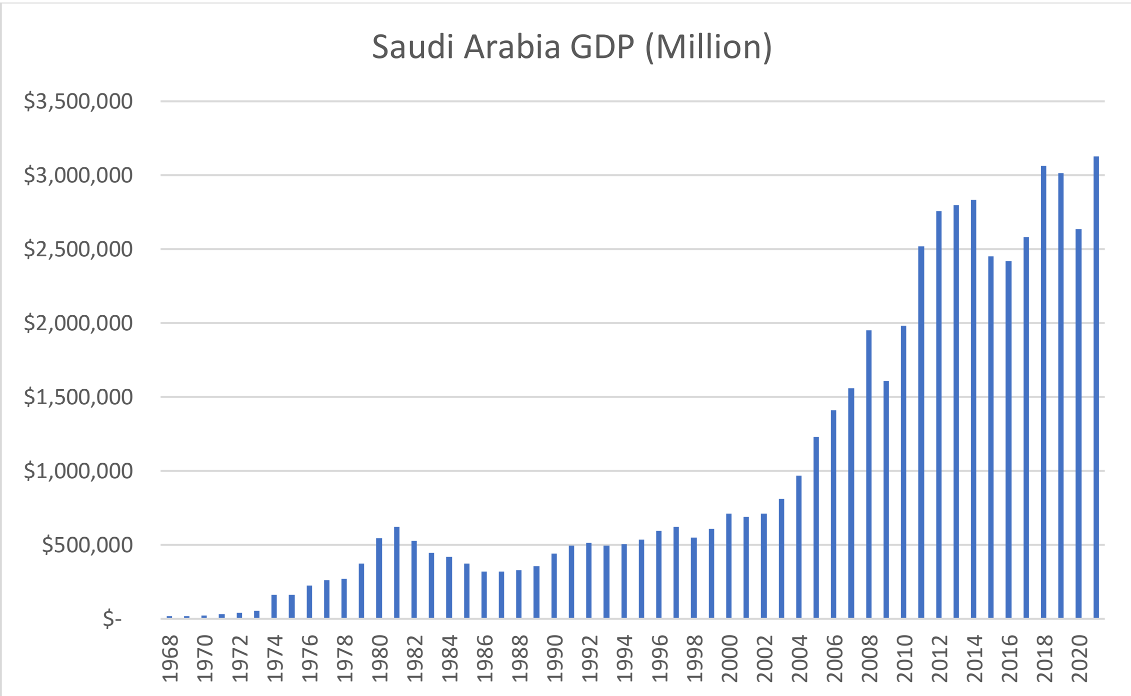
Saudi Arabia is an important player in the global oil market and has a long history of producing and exporting oil. The country boasts the second-largest proven crude oil reserves in the world, representing 21.9% of total OPEC reserves and almost 17.85% of the world's total reserves. It is a founding member of OPEC and the largest oil producer and exporter in the organization, producing 10,478,000 million barrels per day in 2022. Oil-based income accounts for a vast majority of the country's public revenues - around 90%.

Despite this, the 2014 oil crisis had a severe impact on the Saudi government's income, which had steadily increased over the previous six years. To combat this, the government implemented far-reaching reforms and policies to redirect the economy and place it on a more solid foundation. Fortunately, the government had wisely accumulated financial reserves of US$737 billion prior to the crisis, which helped it cope with the situation. However, by August 2017, these reserves had dropped to US$492 billion due to funding necessary activities.

2.3.2 Macroeconomics Overview

The Kingdom of Saudi Arabia's GDP is one of the most important macroeconomic indicators, and it expanded from US$4.188 billion in 1968 to over US$1 trillion by 2022, which is the peak of the Saudi GDP. In 2014, GDP reached US$756.35 billion for the first time before falling in 2015 caused by the oil price decline. Which indicates that both growth and decline of Saudi economy mainly came from the oil industry. Another macroeconomic indicator is the inflation rate (IR), which became negative for the first time in Saudi Arabia in January 2017. The IR reached a new low in May 2017 when it stood at −0.7% before starting to rise again in the following two months to −0.3%.

Figure 2.2: Gross Domestic Product (GDP) in Saudi Arabia between (1969 – 2021)



Source: World Bank (2021).

In 1985, the monetary policy makers in Saudi Arabia made the decision to establish a fixed exchange rate between the Saudi Arabian Riyal (SAR) and the US dollar (US$).

This exchange rate, which is currently set at SAR 3.75 = US$ 1, has been maintained and enforced by the Saudi Arabian Central Bank (SAMA) for the past 38 or so years without any changes to the rate required. This has demonstrated the stability of Saudi Arabia's currency and its commitment to keeping its exchange rate at a reliable rate.

Currently, Saudis do not pay income tax on either an individual or business basis. Instead, citizens pay Zakat (a compulsory religious charity collected by the General Authority of Zakat and Tax) at a fixed rate of 2.5% on the total cash surplus and inventory of tradable goods remaining on hand for a minimum of one year. In contrast, non-Gulf citizens are required to pay a corporation tax of 30%; however, Saudi Arabia announced that a new tax reform in 2018 allows the government to apply a 5% value-added tax (VAT) on selected goods and services. In 2020, the Saudi government increased the VAT up to 15% in response to the economic uncertainty caused by COVID-19 pandemic.

2.3.3 Saudi Vision 2030 and the National Transformation 2023

In order to become independent from oil revenue, Saudi Arabia has implemented a series of five-year plans since 1970, none of which have achieved their desired outcomes (Albassam 2015; Ghafar 2018). In 2015, the decline of oil prices and growth in population prompted the leaders to introduce the ambitious 'Saudi Vision 2030' strategy, which aims to bring about social and economic transformation. This includes economic diversification, development of service sectors such as health, education, recreation and tourism, and the establishment of the world's largest investment fund, the Public Investment Fund (PIF), which will be financed by the sale of 5% of Saudi Aramco.

The vision also sets the goal of increasing non-oil sector exports from 16% to 50%, the private sector's contribution to the GDP from 40% to 65%, and the global rate of foreign direct investment (FDI) from 3.8% to 5.7%. To ensure that the objectives are met, a more detailed five-year plan, the National Transformation 2023, was launched. This plan includes measures to increase spending efficiency, improve asset management, motivate the private sector to make a larger contribution to the economy, and attract FDI into the economy (Kosárová 2020). Furthermore, Vision 2030 proposed developing its financial system mainly through reforming its financial markets to help accomplish its objectives (Alrobian 2020).

In addition to the strategies outlined above, Saudi Vision 2030 aims to diversify its energy sources in order to reduce its reliance on oil. This includes the development of renewable energy sources such as solar, wind, geothermal and nuclear power. It also aims to increase energy efficiency and reduce carbon emissions by increasing the use of clean energy sources. Furthermore, the vision seeks to create economic opportunities for citizens by providing training and education opportunities, investing in infrastructure and technology, and promoting entrepreneurship. Furthermore, the vision aims to improve the standard of living by increasing access to healthcare, housing, and recreational activities. In addition, the vision calls for the reduction of inequality and poverty, and the development of a robust legal system to protect the rights of citizens. Finally, the vision seeks to increase international cooperation and collaboration to promote peace and stability in the region. These initiatives are intended to ensure that by 2030, Saudi Arabia will have achieved its goal of becoming an independent and vibrant economy.

2.4 The Saudi Stock Market

2.4.1 History and Development

The Arab automobile company, according to CMA (2021), was officially the first public company in Saudi Arabia and was established in March 11th 1926. By 1975, the joint stock companies had grown to 14 companies. At that time, shares were traded without governmental or professional supervision. The lack of official regulatory rules lasted until 1984 when a royal decree settled this issue by handing authorised banks in Saudi Arabia the responsibility of trading stocks under the regulatory oversight of SAMA. The first electronic integrated system for trading, called ESIS, was established in 1990. Then SAMA launched a new trading system called Tadawul in 2001. On 31 July 2003, Saudi Arabia announced the Capital Market Law issued by Royal Decree number M/3. Due to the Capital Market Law, a new organisational structure was established. In the same year, stock trading came under the supervision of a new organisation known as the Capital Market Authority (CMA). On 19 March 2007, Tadawul became the only official Saudi stock exchange and was listed as a public company owned by the Public Investment Fund with the CMA acting as the regulator.

2.4.2 Tadawul

Tadawul, as a joint stock company, is the Saudi Arabian Securities Exchange in accordance with Article 20 of the Capital Market Law 2003 and with approval from the Council of Ministers in 2007. The exchange capital amounts to SAR 1.2 billion, divided into 120 million shares with a value of SAR 10 per share. All these shares are owned by the Public Investment Fund. Tadawul is an affiliate member of the International Organisation of Securities Commissions (IOSCO), the World Federation of Exchanges (WFE) and the Arab Federation of Exchanges (AFE). It carries out all listings and trades in securities, deposits, transfers, clearing, settlements and registries of ownership of securities traded on the exchange. It is also the official platform of all market information and announcements; however, the Tadawul exchange has two stock indices: the TASI and a parallel market index called NOMU. TASI is the main stock market index in the

Saudi financial market and is further discussed in the following section. NOMU is a parallel market index that was established on 26 February 2017.

The key differences between the TASI (Tadawul All Share Index) and NOMU (Nomu Parallel Market) indices include different minimum market caps, percentage of shares offered, numbers of public shareholders, disclosure requirements and daily fluctuation limits. For instance, the TASI has a minimum market cap of 100 million SAR, while the NOMU has a minimum market cap of 10 million SAR. Additionally, the TASI requires companies to offer at least 30% of their shares, while the NOMU requires companies to offer at least 20%. Furthermore, the TASI requires at least 200 public shareholders, while the NOMU requires at least 50 public shareholders if the expected aggregate market value for all shares to be listed exceeds SAR 40 million and at least 35 public shareholders if the expected aggregate market value for all shares to be listed is less than SAR 40 million. Moreover, the TASI has standard disclosure requirements, with companies required to disclose quarterly financial statements within 30 calendar days from the end of the period and year-end financial statements within 3 months from the end of the period. The NOMU has less restricted financial disclosure requirements, requiring companies to disclose quarterly financial statements within 45 calendar days from the end of the period and year-end financial statements within 3 months from the end of the period. Finally, the TASI has a daily fluctuation limit of ±10%, while the NOMU has a daily fluctuation limit of ±20%. This difference is important as it allows for greater price fluctuations in the NOMU index. Therefore, the differences between the TASI and NOMU indices are significant and should be taken into consideration when investing in either index.[3]

[3] For more details refer to **https://www.tadawul.com.sa.**

2.4.3 TASI Overview

TASI is the main stock index in Saudi Arabia. As of 2015, TASI began using NASDAQ'S X-Stream INET as a trading system. The method used to calculate the index is as follows:

$$Index = \frac{\text{CDTFFMC}}{\text{PDTFFMC}} \times IP_{t-1} \qquad (2.1)$$

Where IP_{t-1} refers to the index value from the previous day; CDTFFMC is total free float market capitalisation; and PDTFFMC is the previous day's total free float market capitalisation.

This index comprises 20 market indices and sectors (see Table 2.1 for more details) and contains 181 listed firms. TASI reached its highest valuation at 20,634.86 points in 2006. In the first half of 2017, the index stood in the range of 7,000 points; however, in 2006, the CMA applied a new regulation whereby all public companies must have their shares valued equal to SAR 10 instead of the previous value of SAR 10 per share.

Table 2.1: Tadawul Market Structure

#	Market Sector	#	Market Sector
1	Energy	11	Food & Beverages
2	Materials	12	Health Care Equipment & Svc
3	Capital Goods	13	Pharma, Biotech & Life Science
4	Commercial & Professional Svc	14	Banks
5	Transportation	15	Diversified Financials
6	Consumer Durables & Apparel	16	Insurance
7	Consumer Services	17	Telecommunication Services
8	Media	18	Utilities
9	Retailing	19	REITs
10	Food & Staples Retailing	20	Real Estate Mgmt & Dev't

Source: Adapted by the researcher from: https://www.tadawul.com.sa

2.4.4 The Saudi Stock Market: Key Statistics

The Saudi Arabia stock market has been a lucrative investment opportunity for international investors in recent years due to its impressive rates of growth and the compliance of its market policies to international standards. As shown in Figure 2.3, the TASI has experienced ups and downs since 1998. Its highest point was nearly 20,000 points, which was reached before the crash in 2006. This crash was the most severe in the TASI history. During 2007-2008, the Tadawul All Share Index (TASI) experienced a surge, going from around 7,000 points to 11,000 points due to the Global Financial Crisis (GFC). Unfortunately, the next year brought an oil price decrease, which caused the TASI to plunge by almost 50%. From 2010 until the mid of 2014, the TASI experienced a steady growth due to the increasing price of oil. However, a drop in the oil market from 2014 to 2016 caused the Saudi index to plummet, dropping almost 5,000 points.

From 2016 to 2020, the market capitalisation of TASI surged from around 6,911.76 billion to 8,689.53 billion, likely due to the Saudi government's plans to reduce dependence on oil revenues and stabilise the energy market, as evidenced by the signing of the OPEC+ agreement. In 2020, the COVID-19 pandemic had a major impact on the financial markets, yet the value of the TASI still rose by 3.6%, despite the decreased volume of 7.2%. Further, the Saudi Arabian stock market has witnessed a remarkable rise in 2021 causing it to surpass the 10,000 benchmark for the first time since 2014. Contributing to this growth is the increased foreign investments, the reactivation of the OPIC+ agreement, and the repatriation of capital to the country from global financial markets due to the pandemic's ramifications.

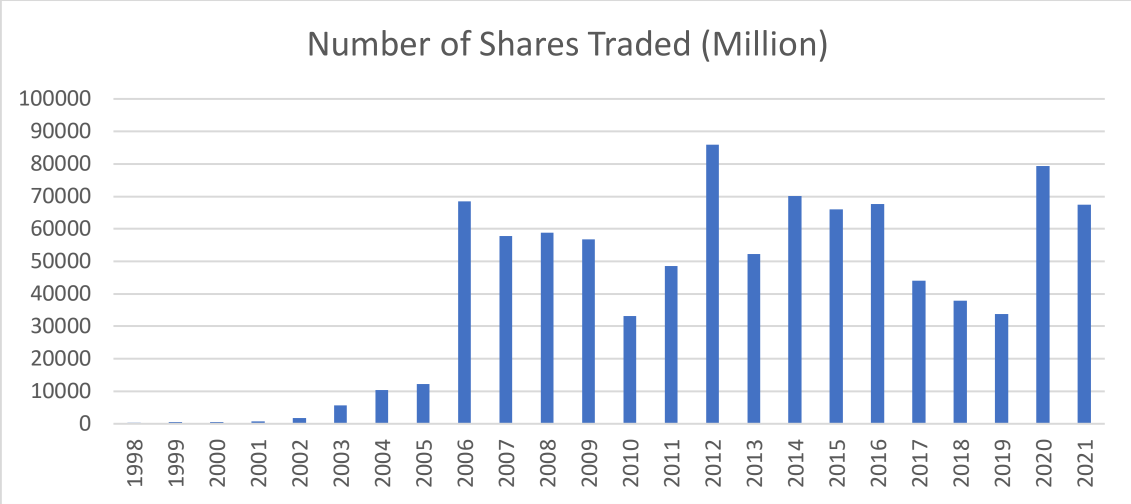
Figure 2.3: Tadawul all shares index (TASI) Performance (1998 – 2021)

Note: this chart is imported from argaam.com. [4]

As shown in Figure 2.4, the number of shares traded has seen an increase over the years, with a peak of 86,006 million shares traded in 2012. After a slight decrease in 2013, the number of shares traded increased again in 2014 and 2015, reaching 70,118 and 65,920 million shares traded respectively. In 2016 and 2017 the number of shares traded decreased again, reaching 67,729 and 43,969 million respectively. However, since then, the number of shares traded has been on the rise with an increase of 33,850 million in 2019 and 79,320 million in 2020 during COVID-19 year. This trend looks set to continue into 2021 with 67,530 million shares traded annually.

Figure 2.4: Tadawul number of share traded (1998 – 2021)

[4] The research imports the chart from an official information provider for Saudi stock market; *www.argaam.com*



Note: this chart is prepared by the researcher based on Tadawul data.

2.5 Saudi Stock Market and Liberalisation Reforms

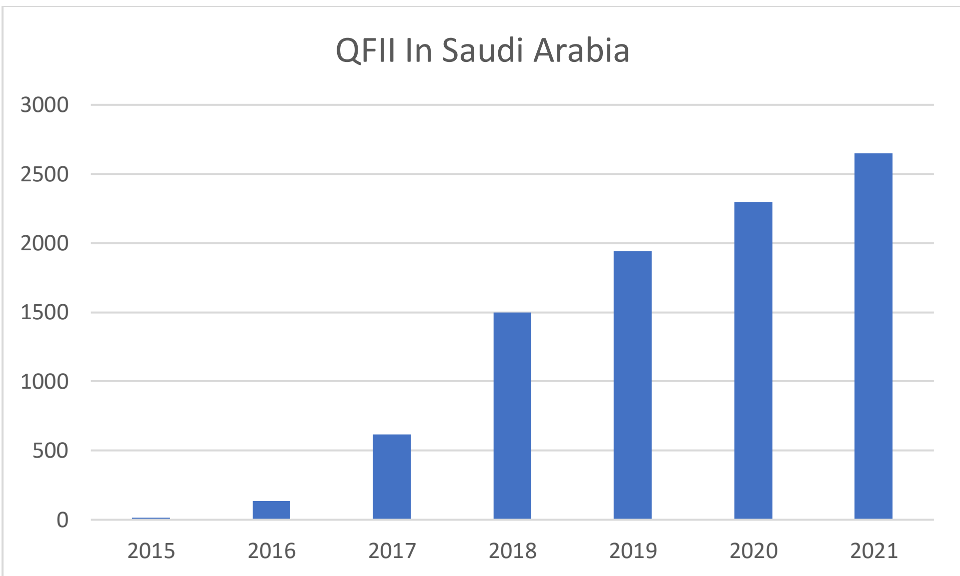
In order to increase the appeal of its stock market (Tadawul) to foreign investors, Saudi Arabia has implemented a number of reforms. These are mainly divided into two programs: the Qualified Foreign Institutional Investors Program (QFII) and the Stock Market Reclassification Program (SMR). The QFII program seeks to encourage foreign institutional investors to invest in the Tadawul by offering them incentives, such as the ability to remit dividends and profits in the currency of their choice. The SMR encourages the development of a more efficient market structure by introducing new regulations, such as the introduction of a new market maker regime, capital adequacy requirements, and corporate governance rules. These reforms are expected to create a more attractive market environment and help attract more foreign investment into the Tadawul.[5]

[5] See Tadawul Annual Report (2018).

2.5.1 QFII Program

Before the launch of the QFII reforms program in May 2015, participation in the Saudi Stock market Tadawul was only available to domestic (individual and institutional) investors and not permitted for foreign investors. The CMA in Saudi Arabia introduced the QFII program to allow foreign institutional investors to own up to 25% of any listed company in the Saudi stock market. In September 2016, CMA further liberalised the reforms, increasing the foreign institutional investors' ownership limit from 25% to 49% of each listed firm. In June 2019, the regulator eased registration requirements to attract more QFIIs and by October 2019, approximately 1,500 global investment institutions had joined the Saudi market as qualified foreigner investors. To register, applicants must have an asset value of at least $500 million per investor. By the end of 2021, more than 2,600 Qualified Foreign Institutional Investors (QFIIs) had been registered and granted licenses to invest in Saudi Arabia, marking a significant milestone in the country's development of its financial sector (see Figure 2.5).

Figure 2.5: Number of QFIIs in Saudi Arabia (from 2015-2021)



Source: Tadawul (2021).

2.5.2 Reclassification Program

As an additional step to modernise the Saudi stock market, the Tadawul authority has sought to upgrade the stock market status from a standalone market to an emerging stock market. This step aims to prompt large global capital flow into the local Saudi stock market. To achieve this reform, Tadawul has implemented conditions and requirements by global index compilers, such as changing trade settlement times from (T+0) to (T+2). Saudi firms must also adapt the international accounting standards by IFRS to become aligned with the international markets included in global indices. Additionally, the divertive market has been established to fulfil the global indices conditions.

Consequently, the policymakers of the Saudi stock market arranged, consulted and negotiated with the global indices to gain international investor recognition (Tadawul 2018). The global indices were assessed and reviewed by Tadawul before they voted to upgrade the stock market status in their annual meeting (FTSE Russell 2018; MSCI 2018; S&P 2018). In March, June and July 2018, Tadawul joined three of the largest global indices for emerging markets: FTSE Russell, MSCI and S&P, respectively. The stock market administration commenced the inclusion of Saudi stocks in their emerging markets index in 2019 (FTSE Russell 2018; MSCI 2018; S&P 2018).

2.6 Conclusion

Since its foundation, the Kingdom of Saudi Arabia has gone through several phases of economic development, including the capital and financial markets. To promote economic growth and stability, attract foreign investors and provide future employment opportunities for the increasing Saudi workforce, the government has implemented a modernisation and industry diversification program as part of its Vision 2030 initiative. This chapter provides an overview of the history, politics, economics, culture and society of Saudi Arabia, as well as the regulatory (liberalisations) reforms, structures and regulations that shape the stock market, such as the index and its industries and the par value of issue share. Moreover, this chapter assists in understanding the methodology chapter.

CHAPTER 3: LITERATURE REVIEW

3.1 Introduction

This chapter presents a review of the literature, mainly covering stock market development. Section 3.1 defines volatility and its characteristics, including clustering, asymmetrical effect, persistence and spillover. Section 3.2 discusses liberalisation reforms and volatility spillover theory. Section 3.3 reviews the empirical evidence on volatility spillover and stock markets (both developed and emerging), including the volatility spillover caused by changing oil prices and some recent events like COVID-19. Sections 3.4 and 3.5 presents the empirical evidence on the effects of foreign ownership and global index reclassification, respectively. Section 3.6 extends the discourse to the effect of social norms and religious principles on the stock market. Section 3.7 underlines the discussions and developed hypotheses of financial reform in the Saudi market context. Section 3.8 discusses the implications of the volatility spillover on the portfolio management. Finally, section 3.9 concludes the discussions in this chapter and identifies the gaps in the literature that this thesis tries to fill.

Over the past few decades, the most active and productive topic of research in the time-series econometrics and finance literature has been stock market efficiency. Fama's (1965) efficient market hypothesis assumes that stock prices reflect all available information, including past stock price patterns, company information and economic status. If this is indeed the case, liberalising the capital market would enhance market efficiency because of the increased availability of mandatory market information (Groenewold & Ariff 1998) and the increasing the willingness of voluntary disculsee (Liao et al. 2022). Cable (1995) argues that economic liberalisation results in increased trade freedom, the removal of entry barriers to the banking system, the lifting of controls over interest rates and a more open stock market. According to Farzanegan et al. (2020) liberalisation of an economy also can be an effective tool for policy makers in reduction the size of the shadow economy. However, in terms of the stock market, liberalisation refers to national laws or regulations that allow foreign investors to buy and sell in the local stock market (Henry 2000). Given the key lessons learned from removing restrictions on direct foreign investments (DFI) in local stock markets, Levine and Zervos (1998) argue that liberalisation will increase foreign capital in the stock market, leading to stock market development. In other words, liberalisation may lead to a larger and more liquid, stabilise volatile and integrated stock market that can move towards becoming global (Hoang & Mateus 2023).

3.1 Volatility and its Characteristics

To broaden the understanding of volatility and its characteristics, this section reviews the growing body of research on returns, volatility and cross-market volatility spillover (Izadi & Hassan 2018; Park, Kutan & Ryu 2019; Park, Park & Ryu 2020).

3.1.1 Importance of Volatility

Volatility has become an important topic for several reasons (Daly 1999; Prokopczuk & Simen 2014; Izzeldin et al. 2021). First, if asset prices fluctuate drastically over a period of one day or less, investors may struggle to accept that the reason for these changes is rooted in information about fundamental economic factors. This may erode investor confidence in capital markets and diminish the inflow of capital to equity markets. Second, for individual businesses, firm volatility is a major determinant of bankruptcy. The higher the volatility of a specific capital structure, the higher the probability of default. Third, volatility is a vital factor in determining the bid–ask spread. Higher stock volatility is correlated with a wider gap between the market marker’s bid and asking prices. Therefore, stock volatility affects the liquidity of the capital market. Fourth, volatility affects hedging strategies such as portfolio insurance, which will increase in price. Fifth, economic and financial theory assumes that consumers are risk averse; thus, the increased risk associated with a specific economic activity should reduce participation in that activity, adversely affecting investments in the capital market. Finally, with increased volatility over time, regulatory agencies and capital providers may compel firms to allocate a significantly larger percentage of their available capital to cash-equivalent investments, potentially harming systematic allocation (Daly 1999).

3.1.2 Definitions of Volatility

Volatility is an important concept in the financial literature (Aouadi, Arouri & Teulon 2015) and has various definitions. Daly (2008) and Rajhans et al. (2015) define volatility as the variation of a variable over time in terms of direction and magnitude. In statistical terms, volatility is defined as the variance or standard deviation of a variable. In financial terms, volatility refers to the dispersion of an asset's price or returns or the movement of a financial instrument's price over time. According to Shafqat (2017), volatility is a measure of risk, making it a critical term in finance. Erdemlioglu et al. (2012) argue that volatility is a measure of the influence of news on asset values and how markets interpret this critical information. Bollerlev et al. (1992) explain that price volatility drives changes in economic variables such as interest rates, inflation and speculative market prices and can result in unexpected situations such as political unrest and market instability.

Given that volatility refers to the deviation of a measure from its anticipated value, according to Press et al. (2007), it can be measured using various statistics, including a distribution's moments—the weighted averages of standard deviations multiplied by various powers. The first power is used to calculate the expectation or mean, while the second is used to calculate variance. It is a convenient proxy of risk because it quantifies the size of the expected fluctuation around the mean (Press et al. 2007). Thus, volatility is represented by the second power of return or price distribution.

A feature of volatility is that it is not directly observable. While changes in the price of financial instruments are visible, volatility is concealed. For instance, given that a single trading day contains only one observation, daily volatility is not identifiable from prices or returns of one day (Tsay 2005). To measure the volatility of one trading day, minimum of two days observations (returns) is needing in the calculation.[6] Although it is not directly measurable in this case, volatility shares several features with those of asset returns. For example, volatility clusters into periods of high and low volatility and evolves in a continuous pattern. Additionally, it does not diverge to infinity, implying that it is stationary.

Given the abovementioned definitions, volatility may be defined as the changeability of a variable and is related to unpredictability and uncertainty. Although volatility is a fundamental and intuitive concept, numerous factors make its analysis and implementation challenging. As a common indicator of asset vulnerability, volatility is used to evaluate the risk–reward trade-off. The equity market literature shows that volatility is synonymous with risk. Excessive volatility or 'noise' in the equity market reduces the validity of asset prices as a signal of firm value, a concept crucial to the informational efficiency of the market paradigm (Karolyi 2001).

Although volatility has long been shown to be a feature of high-frequency speculative pricing, finance scholars recognise the importance of modelling it. The following sections discuss in detail the complexity of constructing volatility models and the model

[6] For more details about volatility calculation see the methodology chapter.

characteristics used to capture underlying economic and financial time-series data, including volatility clustering, symmetrical and asymmetrical (leverage) effects, volatility persistence and volatility spillover.

3.1.2.1 Volatility clustering

The arrival of news about an equity's fundamental valuation is the most important factor influencing stock market prices. When news arrives with a sufficiently high frequency, returns are likely to reflect volatility clustering (Daly 2008; Engle 2004). According to Cont (2005), large price fluctuations tend to cluster together, resulting in the persistence of price change amplitude. In other words, high volatility follows high volatility, while low volatility follows low volatility (Mandelbrot 1963). Therefore, volatility clustering indicates that stock returns are not independent across time (Cont 2005). Further, Tseng and Le (2011) hypothesised an association between heavy-tailed return distributions and volatility clustering in autocorrelation functions, finding that the degree of volatility clustering was associated with the slow decay pattern in the autocorrelation functions rather than the heavy-tailed return distributions.

There have been numerous studies on stock market volatility clustering (Hussain, Murthy & Singh 2019). For example, Ning, Xu and Wirjanto (2015) examined natural volatility clustering in stock returns using a univariate copulate time-series model and kernel volatility and found that volatility clustering is significantly nonlinear and highly asymmetric. Using ARCH, GARCH, IGARCH and FIGARCH models, Bentes, Menezes and Mendes (2008) empirically demonstrated the long memory and volatility clustering of the stock market in the S&P 500, Nasdaq-100 and STOXX 50 indices. Kalyanaraman (2014) used a symmetric GARCH (1,1) model to explore daily stock market volatility in Saudi Arabia from 1 August 2004 to 31 October 2013, finding that returns of the Saudi stock exchange exhibit volatility clustering and non-normal leptokurtic distributions. In addition, the analysis revealed a time-varying volatility and persistence, indicating that the volatility of the past influences the volatility of the present. Thus, prior returns play a role in current returns.

3.1.2.2 Volatility persistence

According to volatility persistence theory, returns and volatility tend to be a function of their previous values (De Bondt & Thaler 1985). Volatility persistence, also known as 'reversion', challenges the efficient market hypothesis. Indeed, to confirm the return reversion phenomenon, Fama and French (1988) investigated the memory pattern of stock returns, finding that previous stock prices predict future stock prices. This demonstrates a memory pattern in the return and volatility reversion process.

The autocorrelation function of absolute returns, also known as persistence behaviour, has been employed to assess volatility clustering, showing that the level of persistence differs from market to market. The effects of shocks typically last for a long period before the market can return to its normal mean level; thus, returns exhibit volatility persistence. During a period of high clustering, volatility returns to its typical level. Global markets exhibit long-term persistence behaviours, which steadily reduce (Mert 2016). Using hourly intraday returns data and a basic standard deviation and variance technique, Lockwood and Linn (1990) demonstrated a significant increase in the conditional volatility persistence of US stock returns from 1964 to 1989.

Volatility persistence is also driven by derivative contracts such as forwards, futures and options. Antoniou and Holmes (1995) employed a GARCH model with a dummy variable to investigate the effect of futures trading contracts on the UK spot market, finding that volatility persistence slightly declined following the advent of futures trading. Gulen and

Mayhew (2000) reached a similar conclusion in their study of the early days of futures trading in Europe and the US. Using a GARCH model with a dummy variable, Mallikarjunappa et al. (2008) found that volatility persistence was higher prior to the inclusion of futures and options, demonstrating that the advent of derivatives trading had a major impact on volatility persistence. Debasish (2009) employed an IGARCH model to examine the effect of NIFTY 50 futures on stock market volatility in India and reported a decrease in volatility persistence in the post-futures period.

Volatility persistence is also influenced by public news (Chen & Ghysel 2011; Ho et al. 2020; Lamoureux & Lastrapes 1990). Employing a GARCH model with a dummy variable, Janssen (2004) demonstrated that the arrival of public news in the US market was associated with a significant reduction in the volatility persistence of stocks, treasury bills, bonds and the currency market. Additionally, using an ARMA–EGARCH model, Pati and Rajib (2011) demonstrated that trading volume in the Indian futures market affects volatility persistence (rated at 0.98 with an asymmetry coefficient of 0.86), showing that negative shocks increase volatility more so than positive shocks.

Research shows that volatility persistence may be short or long term. Short-term volatility persistence occurs when the effect of an asset's return on its mean value is limited to a 1-month period (Chi et al. 2016; Hart et al. 2015; Ribeiro et al. 2017). In contrast, long-term volatility persistence refers to the influence of a stock return lasting for more than 1 year (Ahmed et al. 2018; Bentes 2014). Further, this type of volatility persistence can be estimated using one of two methods: relative mean reversion or absolute mean reversion (Slim et al. 2017; Trypsteen 2017). The number of empirical articles on short-term volatility persistence has risen over time because of increased accessibility to daily market information. As a result, short-term volatility spillover has become more appealing than long-term mean reversion (Chaves & Viswanathan 2016; Huang 2017; Neaime 2015; Wang et al. 2015).

3.1.2.3 Asymmetry (leverage)

A major assumption of stock market volatility is that it tends to be asymmetric. Asymmetrical reactions can be identified when bad news (negative information) leads to more volatility than does good news (positive information). According to Bekaert and Wu (2000), the leverage effect is associated with asymmetry when stock market returns are negatively correlated with conditional volatility. In this regard, the asymmetrical aspect of volatility can be statistically determined using various asymmetrical GARCH models such as the widely used EGARCH and GJR-GARCH models (Ali 2013). For instance, Antoniou et al. (1998) employed a GJR-GARCH model to examine the asymmetry effect in three stock markets, finding that investors' reactions to bad news compared with good news led to greater reductions in the market.

Many scholars have investigated the volatility asymmetry in developed stock markets. For example, Bayraci (2007) analysed the UK stock market using GARCH, EGARCH and APARCH models, finding that EGARCH outperformed the other symmetrical models and captured a significant asymmetric coefficient (−0.0355). Yang and Chang (2008) investigated stock markets in the US, Japan, Singapore, South Korea and Taiwan using a threshold GARCH (TGARCH) model. They found similar results to those of Bayraci (2007) in which the coefficient for bad news was higher than that for good news in the respective stock markets.

Analysing the volatility of the Indian stock market using EGARCH, Banumathy and Azhagaiah (2015) also found asymmetrical effects with a significant coefficient (−0.0906). These findings were replicated by Tanty and Patjoshi (2016), who demonstrated that negative information generates more volatility than does positive information. In addition, Bagchi (2017) employed an APARCH model to examine asymmetrical behaviours in the crude oil and BRIC (Brazil, Russia, India and China) stock markets. The resultant leverage coefficients (crude oil: 0.99; Brazil: 0.99; Russia: 0.87; India: 0.61; China: 0.68) confirmed the asymmetric volatility in these markets.

There has been a growing number of studies on asymmetric volatility in the Middle East and North Africa (MENA). For example, using multiple univariate models in the GARCH family to identify both symmetric and asymmetric specifications, Abdulla (2012) investigated stock return volatility in the Saudi market from 2007 to 2011 based on the daily closing prices in the general market index. The symmetric models revealed a positive correlation between volatility and returns, while the asymmetric GARCH models revealed asymmetry in the returns of the general Saudi stock index, confirming the presence of the leverage effect in index returns.

In contrast to the abovementioned papers, some studies have generated different outcomes regarding asymmetrical stock market volatility. For instance, Al-Najjar (2016) compared the ARCH, GARCH and EGARCH models to investigate stock return volatility in the Amman Stock Exchange (ASE) in Jordan from 1 January 2005 to 31 December 2014, finding that the symmetrical ARCH and GARCH models were superior to the asymmetrical EGARCH model for capturing characteristics of the ASE and providing evidence of both volatility clustering and leptokurtic distributions. In contrast, the EGARCH model generated no significant evidence supporting the existence of an asymmetric (leverage) effect in stock return volatility in the ASE.

Investigating the Saudi stock market, Mhmoud and Dawalbait (2015) found that both the GJR-GARCH and EGARCH models performed better than the simple GARCH model, with the Akaike information criterion (AIC) and maximum log-likelihood criteria supporting their conclusions. The presence of asymmetrical economic and financial shocks suggests that the GRJ-GARCH (1,1) model is superior for forecasting volatility in the Saudi stock market.

In addition, Alghfais (2018) examined daily returns in the Tadawul All Share Index (TASI) to forecast volatility using the simple ARCH, GARCH, EGARCH and TGARCH models. The asymmetrical EGARCH (1,1) model performed better than all other models in forecasting the volatility of the Saudi all shares index returns in the short term, while the symmetric GARCH (1,1) model showed better performance than all other GARCH family types in estimating the volatility of Saudi stock market returns in the long term.

3.1.2.4 Volatility spillover

This section focuses on the various concepts of volatility spillover. Pugel (2016) argues that financial integration causes volatility in one market to respond to innovation in other markets and that the interdependence between countries and rapid growth of cross-border volatility spillover have become highly significant. Moreover, volatility spillover effects reveal the relationships between economic events and financial markets (Abu Hasan 2017; Antonakakis, Floros & Kizys 2016; Gkillas et al. 2021; Karali & Ramirez 2014).

Yilmaz (2010) found that cross-economy shock transmissions during the 2008 global financial crisis (GFC) caused a substantial spike in stock market volatility, which spread across markets. Moreover, Guhathakurta, Dash and Maitra (2020) identified volatility spillover as a primary area of concern for scholars, practitioners and policymakers. They contend that investigating volatility transmission involves examining the presence of volatility spillover, network connectedness, the degree to which markets are interrelated and how vulnerable they are to stress in other markets.

In an assessment of market interdependence, Rigobón (2019) proposed that volatility spillover occurs in both positive and negative circumstances. Additionally, Wegener et al. (2018) demonstrated the spillovers from explosive regimes to highlight crisis migration, in which one crisis produces another. Volatility connectedness refers to the dynamic and directional nature of volatility spillover across different assets or markets (Diebold & Yilmaz 2015). As previously stated, financial integration causes markets to react to advances in other markets. Financial crisis researchers (e.g. Gallo et al. 2012) have questioned whether crises beginning in one market and spreading to others are the consequence of a spillover effect or an interdependent response to a common shock.

Diebold and Yilmaz (2009) argue that spillovers exist in the form of returns and volatility and are typically connected with risk. Additionally, Bekaert et al. (2014) established that shock transmissions cannot be described by fundamentals such as banking, trade, or financial linkages. Engle et al. (1990) define volatility spillover in terms of the cause of variance between two financial markets. Similarly, Rigobón (2016) and Shafqat (2017) argue that a volatility spillover occurs when a positive or negative shock in one market is transferred to other markets.

Cornes and Sandler (1986) contend that spillover occurs unintentionally and moves from market to market incidentally. The theory of volatility spillover originates from the work of Engle et al. (1990), who identified volatility spillover as the cause of market variances and emphasise that international returns may significantly affect local returns. The authors also discuss two types of spillover, one caused by local returns and the other by cross-border returns. In the first type, also known as volatility clustering or the heatwave effect, current market volatility is a function of its previous volatility. In contrast, the second type (cross-border spillover), also known as the meteor shower effect, asserts that current market volatility is a function of the previous volatility of that market as well as external markets (via volatility transmission). The empirical findings of Engle and Susmel (1993) support the spillover theory in which all stock markets exhibit volatility clustering.

For Diebold and Yilmaz (2015), volatility connectedness is a way of measuring the dynamic and directional characterisation of volatility spillover between multiple assets or markets. Further, Wu (2001) argues that when market interdependence is strong, volatility spillovers across markets tend to increase in magnitude. When volatility increases, market returns are more strongly correlated, and periods of high volatility are associated with market crashes. As Diebold and Yilmaz (2012) point out, market volatility associated with a crisis often leads to volatility spillover across markets.

As discussed above, volatility spreads across assets and markets through spillovers. Therefore, it is rational to assume that volatility spillovers also have asymmetric characteristics. Similar to the asymmetry in volatility, asymmetry may also be present in volatility spillover based on the type of news being released. Compared with good news, bad news appears to have a greater effect on both local and cross-market spillovers. Hence, both volatility and volatility spillover can inform risk assessment and portfolio diversification strategies (Garcia & Tsafack 2011). Bartram et al. (2012) suggest that by investigating asymmetry, it may be established whether volatility was caused by good or bad news. Therefore, the asymmetrical effect can have various impacts on asset valuation (Segal et al. 2015).

3.2 Liberalisation Reforms and Volatility Spillover Theory

Previous studies mostly demonstrate a direct relationship between stock market development and economic growth. For instance, in their analysis of 67 studies, Valickova, Havranek and Horvath (2015) emphasise that compared with other financial markets, stock markets support faster economic growth. Previous studies have also identified macroeconomic and institutional factors as the main determinants of stock market development (Billmeier & Massa 2009).

Institutional reforms such as liberalisation and modernisation, which aim to attract foreign capital into local stock markets, positively contribute to stock market development and economic growth. Levine's (2002) pioneering study showed that international financial liberalisation improves domestic banking systems and increases stock market liquidity and economic growth. Bekaert, Harvey and Lundblad (2011) found that economic growth resulting from liberalisation is permanent rather than temporary. The findings of Batuo, Mlamb and Asongu (2018) support those of Levine (2002) and Bekaert, Harvey and Lundblad (2011), suggesting that financial liberalisation has had positive effects on financial stability and economic growth in 41 African economies.

Several authors have reported that liberalisation is not always positively correlated with economic growth. Yanikkaya (2003) investigated the relationship between economic growth and liberalisation, revealing that trade barriers are associated with economic growth in developing economies.[7] In line with Yanikkaya (2003), Adams and Opoku (2015) found that foreign direct investment had no significant effect on economic growth in 22 sub-Saharan African countries.

In recent decades, there has been increased integration between global investment markets and various financial segments, which have had a significant effect on the financial market. The movement of financial streams changes the composition of political

[7] An analysis of economic growth is beyond the scope of this research project.

forces. Thus, the influence of financial liberalisation may be both unidirectional and bidirectional (Xiong & Han 2015).

The integration of capital markets and other segments of the investment market is a natural process. The strengthening of economic relations between countries at different levels of development, the exchange of information and technologies, the liberalisation of currencies, legislation, the transition of many countries towards a single currency (the euro) and widespread property protection rights have accelerated the movement of item and cash streams between markets, ultimately leading to the formation of global and regional financial centres (Mikhaylov 2018). Important factors contributing to the integration of world markets have included the elimination of barriers to the free movement of capital and the integration of stock exchanges (including the trading systems of national exchanges, cross-exchange agreements on unified trading rules, company requirements, providing information and cross-listing companies). Accordingly, any significant news event is reflected in both local and geographically distant financial markets (Mikhaylov 2018).

The primary investment characteristics of stock markets include profitability, hazards (volatility) and liquidity (the size of the market and its ability to maintain price equilibrium when making significant transactions with low transaction expenses). More complex characteristics that are recently being considered by global investors include the degree of integration of the local market with the global capital market and, more generally, the global financial market (Adam et al. 2016). Adam et al. (2016) also discuss the effect of volatility spillover when the local market is not independent and is subject to considerable external influences. Maitra and Dawar (2018) assessed the extent to which the local market is affected by more influential markets, how this effect changes over time and the presence of any mutual effects. This thesis addresses novel research questions, including the dynamic correlations between markets, the effect of volatility, changes in markets over time and disturbance centres at regional and global levels (Maitra & Dawar 2018).

The level of integration of financial markets is mainly relevant to international investors. When making investment decisions, knowledge about the interconnections between local markets is essential to diversify investment portfolios and minimise risk. Estimates of the dynamic correlations between markets and the degree to which the local market is included in the financial system may be used to develop optimal investment portfolios and hazard hedging strategies (Kumar et al. 2017). Meric et al. (2016) argue that despite the diminishing opportunities for cross-country portfolio diversification because of an increase in market relations, there are still opportunities for investors to engage in cross-country portfolio investment.

Market integration has a significant impact on the financial stability of individual countries; therefore, knowledge regarding the behaviours of markets and their segments (e.g. industries) and the source of shocks can help regulators control the behaviours of markets during crises. The research presented in this thesis is relevant to the 2008–2009 GFC. An investigation of the dynamic correlations between markets will enable global and local investors and regulators to create policies based on a holistic view of the world and the changing balance of power and to estimate the likelihood that a portfolio will generate the expected yield (Ben Slimane et al. 2013).

Investigations that posed questions about the quantitative estimation of the degree of integration between stock markets (indices) were mainly conducted in the 1960s–1970s. The key conclusion of these works is that correlations between stock indices are weak

(Granger et al. 1970; Panton et al. 1976). Events in national markets have a major influence on stock market behaviours and the values of stock indices of the countries in question. However, these conclusions changed in the mid-1980s. A popular area of research is the effect of news from one market on investment returns in other capital markets. Studies have confirmed that since the mid-1980s, the US market has become a global financial centre that determines the dynamics of stock markets in other countries. For example, Eun and Shim (1989) applied a vector autoregression model (VAR) to identify dependencies between the world's largest markets: Australia, Canada, France, Germany, Hong Kong, Japan, Switzerland, the UK and the US. The authors concluded that events in US markets strongly influenced the behaviour of indices of other exchanges, while no other market explained the changes occurring in the US market.

Given that most findings emphasised the unique role of the US stock market, researchers were forced to pay attention to the time lag between the arrival of news and the reaction of foreign markets. Lin, Engle and Ito (1991) used daily and nightly data to compare the volatility and profitability of the Japanese and American indices, finding that the daily values of the indices in each market were associated with the corresponding nightly values of another market. Another critical aspect of the relationships between markets is the effect of individual market liberalisation on the degree of integration. Kim and Rogers (1995) used a GARCH model to analyse stock index dynamics of three countries—South Korea, Japan and the US—finding that the relationship between the Japanese and US markets increased when the South Korean government allowed foreign institutional investors to purchase shares of national companies.

Since the mid-1990s, the number of studies on the ties between geographically distant stock markets has increased. For example, using an EGARCH model, Booth et al. (1997)

showed a significant integration between the markets of Scandinavian countries (Denmark, Norway, Sweden and Finland). The Asian financial crisis of 1997–1998 resulted in several studies on the effects of changes in Asian markets, including those of Hong Kong and Taiwan, on markets in Europe, the US and Latin America.

3.3 Volatility Spillover and Stock Markets

This section reviews the literature on spillover volatility between two or more financial markets. The discussion initially focuses on the spillover between developed stock markets before focusing on spillover between emerging stock markets. Finally, studies on spillover of volatility between the commodities (oil) markets and the stock markets are reviewed.

3.3.1 Developed Stock Markets

Investigating the effect of macroeconomic shocks in one country on the stock markets of other countries is critical when assessing the integration of global financial markets. While the capital markets of developed countries are becoming increasingly integrated, not all emerging markets have entered into the global financial system (Nikkinen et al. 2006). Knowledge of the degree of exposure of the local stock market to changes in other markets allows international investors to diversify their investment portfolios and hedge their bets by purchasing emerging market securities. According to Meric et al. (2016), this probability exists even for global financial leaders (i.e. the US, Japan, the UK, France and Germany). In early works, King and Wadhwani (1990) and Martens and Poon (2001) empirically conclude that the integration of capital markets exists in terms of both profitability and volatility.

Works that posed questions about the quantitative estimation of the degree of integration between stock markets (indices) were mainly conducted in the 1960s–1970s. The key conclusion of these works is that the correlation between stock indices is weak and events in national markets have a major influence on the values of stock indices of the countries under consideration. However, the mid-1980s saw a change in the perspective of researchers, who argued that markets were integrating, and the US was playing an increasingly important role as a global financial centre and was determining the dynamics of other stock markets. (Scientific works were mostly based on testing the impact of news from one market on changes in investment returns in other markets.) Among the subsequent writings of the 1990s, Hamao et al. (1990) noted that the US influences both the profitability and the volatility of other markets. Attention has also been focused on the strength of the reverse effects of developed regional capital markets such as Germany, the UK and Japan on the US stock market. In contrast to the research on developed markets, the research on emerging capital markets is limited, possibly because of the traditional assumption that these markets have an independent influence on other markets. To identify such interactions, the GARCH model and its modifications have been applied to daily or weekly return stock indices. The 1990s were marked by the emergence of scientific papers on market integration through the analysis of volatility between developed markets (Hamao et al. 1990; Richards 1996; Tanizaki & Hamori 2008; Weber & Zhang 2012).

The creation of the European Union (EU) and the crises of the late 1980s generated a large number of studies on integration within the European stock market. Several studies have demonstrated the dominant role of the German market in the region and that shocks in the German financial market have a significant impact on other European financial markets (Alikhanov 2013).

Various studies, including those conducted in the late 2000s, have demonstrated the dependence of stock markets on the US market, as estimated by models in the GARCH family. Using a copula-GARCH model and a multidimensional GARCH–BEKK model, Xiao and Dhesi (2010) tested the dominant role of the US stock market using the daily closing prices in the Financial Times Stock Exchange 100 (FTSE 100), CAC, DAX and S&P 500 indices from 5 January 2004 to 1 October 2009. The authors showed that the US stock market is the primary source of volatility change for the European and Asian markets.

Balasubramanian and Premanatra (2003) examined the daily returns in the Hang Seng Index (Hong Kong), the Nikkei 225 (Japan), the Straits Times Index (STI) (Singapore), the FTSE 100 (Great Britain) and the Dow Jones Industrial Average (US) for the period 1 January 1992 to 26 August 2002. Using one-dimensional and multidimensional GARCH models and a VAR, the authors found an abnormal state of integration between the US market and the Hong Kong and Japanese markets. They also demonstrated a subtle effect flowing between Asian markets, specifically Hong Kong and Japan. Based on an analysis of the weekly indices of Australia (All Ordinaries), Singapore (STI), Great Britain (FTSE 100) and the US (S&P 500) from 6 January 1992 to 21 June 2009, Karunanayake et al. (2010) found a significant volatility spillover from the US market to the UK, Singapore and Australia markets using an MGARCH model for the analysis.

Using daily data and a one-dimensional EGARCH model, Koutmos and Booth (1995) examined the links between the Tokyo, New York and London stock exchanges for the period 3 September 1986 to 1 December 1993 and confirmed a volatility spillover between all three markets. Using a stochastic volatility model for data from 2 April 1984 to 2 February 2007, Tanizaki and Hamori (2008) investigated the presence of volatility spillover between Japan, the UK and the US, finding a reciprocal volatility spillover effect between the US and the UK and between Japan and the UK.

The UK market is the primary source of volatility in the European market (Xiao & Dhesi 2010). Several works have demonstrated the interdependence of European markets following the introduction of the euro. Susmel and Engle (1994) analysed the relationship between the US (S&P 500), Germany (DAX 30), the UK (FTSE 100) and France (CAC 40) in the period 3 December 1990 to 6 August 2004 using a multidimensional EGARCH model, concluding that the US market influenced the UK and Germany markets, and the correlation between European markets has strengthened since the introduction of the euro.

Using GARCH-type models, several works have demonstrated the enormous influence of the Japanese and Hong Kong markets on other Asian markets. For example, Ng (2000) was among the first to test the influence of the Japanese and US markets on the markets of Hong Kong, Korea, Malaysia, Singapore, Taiwan and Thailand. Using a GARCH model and weekly data, the author found that the Japanese and American markets had a statistically significant effect on all listed markets. Another study by Johnson and Soenen (2002) demonstrated that the five largest Asian markets (China, Hong Kong, Malaysia, New Zealand and Singapore) and Australia had a significant spillover effect on the Japanese economy. The authors considered the daily closing prices of the Morgan Stanley Capital International (MSCI) stock index for the national stock markets of Australia, China, Hong Kong, Malaysia, New Zealand, the Philippines, India, Indonesia, Japan, Korea, Singapore, Taiwan and Thailand from 1988 to 1998 using the log-likelihood ratio developed by Geweke (1982).

Other studies have identified volatility spillover in other financial markets such as local and global stock market indices. Bissoondoyal-Bheenick et al. (2018) analysed the volatility spillover between the Australian market and the US and Chinese markets from 2007 to 2016 and found a bidirectional volatility spillover between the stock market indices of these countries.

Chuang et al. (2007) investigated six markets in East Asia—Japan (Nikkei 225), Hong Kong (Hang Seng Index), Singapore (STI), South Korea (Seoul Commodities), Thailand (SET Index) and Taiwan (TAIEX)—for the period 3 January 1992 to 10 June 2006 using a GARCH–BEKK model. The study found that the Japanese market was weakly dependent on the markets of other Asian countries but is the primary source of volatility among them. A similar result was later demonstrated by Lee (2009) using a VAR–GARCH model for six Asian markets: China, Hong Kong (Hang Seng Index), South Korea (Korea Composite Stock Price Index), Japan (Nikkei 225), Singapore (STI) and Taiwan (Taiwan Weighted Index) for the period 1 January 1985 to 31 December 2004.

Recently, number of empirical researches related to the volatility spillover between developed stock markets and other commodities markets is increasing. For instance, Balcilar et al. (2021) examined the volatility spillover between the S&P500, oil, and gold from January 1986 to August 2018 using a VAR analysis. The study found that in the full period, the S&P500 and crude oil acted as net transmitters of returns spillover while gold was the net receiver. However, the results of the sub-periods showed that gold became a net transmitter of returns spillover while crude oil was the net receiver.

Another study by Kahraman and Keser (2022) investigated the realised data of the Japanese stock exchange and 12 different Western stock indices from January 2002 to September 2020 using a modified VAR. The study found a high level of spillover between the Japanese stock market and other stock markets, with the S&P500 and AEX acting as net transmitters and the Australian stock market and Nikkei 225 as net receivers. Furthermore, the relationship between markets extended beyond short and medium-term fluctuations and into the long-term.

Additionally, Joshi et al. (2022) used intraday data of the S&P500 and cryptocurrency market from June to December 2020 and employed the MGARCH-BEKK model to analyze volatility spillover. The study found evidence of an asymmetrical effect on both the S&P500 and cryptocurrency markets during the COVID-19 pandemic, with the cryptocurrency market having a unidirectional effect on the S&P500's volatility.

Lue et al. (2023) examined intraday data of WTI and China's stock and commodity futures markets from April 2010 to May 2018 using the MHAR-CSV-t model. The findings of the study revealed that WTI was the most volatile market among the ones studied, with Corn, Gold, and Equity acting as persistent transmitters of volatility shocks. Copper, on the other hand, was identified as a net receiver of these shocks. WTI was found to take on both roles, acting as both a transmitter and receiver of volatility shocks across markets.

3.3.2 Emerging Stock Markets

The recent trend towards strengthening the economies of developing countries has significantly increased the importance of analysing the volatility of markets in these countries. However, before discussing the current volatility of emerging markets, it is important to present the historical background and trends of developing markets based on retrospective volatility data, including against the backdrop of global economic crises and the volatility of developed economies.

In January 2018, Danielsson et al. (2018) assessed the effect of volatility on the likelihood of financial crises over the past 211 years and across 60 markets. The authors concluded that volatility per se is not always a precursor of global economic shocks; however, extraordinarily high or low levels of volatility can foreshadow a crisis because they are indicative of growing political, economic or financial uncertainty. Baker et al. (2016) and Gulen et al. (2016) found that political uncertainty leads to high stock volatility, resulting in a reduction in investment and production and an increase in unemployment, and low volatility may lead to a crisis in the banking system. The analyses also indicated that the link between volatility and currency crises is virtually absent (except for periods of war).

The emerging Russian market has also been included in a minimal number of studies on volatility spillover. Using a VAR–GARCH model to analyse weekly stock market data, Caporale and Spagnolo (2012) showed a volatility effect flowing from Russia and Great Britain to Central and Eastern Europe countries (the Czech Republic, Hungary and Poland); however, no reverse influence was identified. Employing a GARCH–BEKK model, Saleem (2009) showed that before the 1998 crisis, there were bilateral volatility effects between Russia and the US and emerging markets in the European region and unilateral volatility effects from EU markets to the Russian market. During the 1998 crisis, there was a unidirectional volatility effect flowing from Russia to all other stock markets as well as from Asia to Russia. However, following the 1998 crisis, bidirectional volatility effects flowed between Russia and the US and Asian markets. There was also a unidirectional volatility effect from Russia to emerging European markets (Saleem 2009).

Weber and Zhang (2012) used daily national index data from 1 February 1992 to 30 May 2008 to analyse the influence of the Chinese stock market on Brazil, India, Malaysia, Thailand, Poland and Hungary. Using a cointegration analysis and an the structural dynamic conditional correlation (SDCC) model, the authors showed that the Chinese stock market had an assimilative effect on these countries. The correlation coefficients were positive for all countries; however, in the long term, the Chinese index did not determine the behaviours of these emerging stock markets. Cointegration vectors between the variables under investigation were not detected.

Fedorova and Pankratov (2010) used an EGARCH econometric model to determine the influence of external factors on the Russian stock market. The model included the profitability of the world's largest stock exchanges in both developed and developing countries (US, China, UK and Germany). The results showed that the profitability of European stock exchanges had a stronger impact on the Russian stock market compared with the US or Chinese markets because of the geographical proximity of European countries, which have historically closer economic relations.

Sarwar (2012) found a strong negative correlation between the volatility index (VIX) and the stock indices of US, China and Brazil from 1993 to 2007. The Russian market reacted more aggressively to the dynamics of the VIX compared with the other countries. The results also demonstrated that this indicator has an asymmetrical effect: investors from all countries reacted more strongly to negative news about the VIX trend. However, other studies showed no evidence of the impact of this indicator on stock markets.

Fedorova and Pankratov (2010) also found a long-term relationship between the Russian stock market and BRIC markets. While this was attributable to the expansion of international trade in goods, services and financial assets, the occasional waves of foreign capital inflow into developing countries and the entry of the largest companies into international financial markets lay the foundation for integration. The link with the Chinese stock index is also easily explained by geographical vicinity and trade volumes, which in 2012 reached a record level. Moreover, according to analysts, this trend will continue in the future. Interestingly, according to the results of the correlation analysis, the Russian stock market was associated with developed countries only during a crisis period.

Other studies have assessed volatility spillovers from exchange markets to stock markets. Jebran (2018) examined the spillover effect before and after the GFC in 2007, identifying a one-way volatility spillover from the currencies exchange market to the Chinese stock market before the crisis. However, volatility spillover become bidirectional between the exchange market and the stock market after the GFC. Jebran (2018) applied a univariate EGARCH approach to record the flow of volatility between the forex market and the Chinese stock market using daily returns from 2002 to 2013.

Yang et al. (2004) reported similar findings based on their examination of the relationship between the stock markets of developing countries and the US market from 1976 to December 2001. According to their correlation analysis, indicator values were high only during a crisis because of dramatically increased market volatility, while developed countries only had an indirect effect on developing countries through the currency and oil markets. Otherwise, this trend was not observed.

3.3.3 Volatility Spillover Between Oil Prices and the Stock Market

The oil trade has recently become the subject of speculative operations on a vast scale. The actions of speculators leave an imprint on the current volatility of markets. Over the past 25 years, the volatility of oil markets has dramatically increased, which impact other markets such as stock markets (Apergis & Miller 2009). According to O'Neill et al. (2008) and Osman et al (2019), the high oil prices can also increase inflation. Therefore, it significantly increases investments that aim to improve oil production to stabilised oil prices. Accordingly, mitigating these negative factors is possible if fluctuations are not too extreme (Gomes & Chaibi 2014).

The European Commission has proposed a tax of 0.01% on financial transaction fees for transactions in the oil market (Europa 2018). However, this tax rate may be too low to prevent speculators from engaging in hazard optimisation. Since the advent of the modern era of oil production in 1859, when the first oil wells were drilled in Pennsylvania, extreme volatility and pronounced cyclicality have become permanent characteristics of the oil market (Cleveland 2009). Compared with the price of goods or services, oil prices are substantially less stable and are similar to other industrial and agricultural assets. Volatility manifests across all periods, from ultra-short (tick and daily fluctuations in prices on futures contracts) to long-term (monthly and annual) periods. Moreover, price dynamics are not chaotic under any condition; they obey the laws of cyclicity in all periods. These are the fundamental characteristics of the oil market (Cleveland 2009).

Prices, production and consumption following a shock do not immediately return to an equilibrium. Eighty years ago, Miron Watkins, a professor of economics at New York University, proposed the main problem with oil: there is always too much or too little. The economist Paul Frankel asserted that the first and most important feature of the oil industry is that it cannot correct and recover on its own. Given the lack of internal restructuring mechanisms, the industry has an inherent tendency towards deep crises, and its success is quickly replaced by complete collapse. All attempts to overcome cyclicality and to achieve more stability have been in vain (Reuters 2017).

On 15 November 2017, the widely traded futures for Brent crude oil, which set a biennial maximum of 64 USD per barrel on 7 November, fell below the US dollar. The US West Texas Intermediate (WTI) price also decreased. This decline coincided with a sharp drop in price in the metal market, mainly because of the fear of a log jam in demand in China. Investor nervousness was also demonstrated by a significant weakening of high-return corporate bonds. Growth resumed, but because it alternated with a fall, prices were quickly adjusted, some amounting to $62 per barrel (Raper 2017). In fact, the turn in the oil market ended the discussion of price increases above $70 per barrel, which intensified after the detention in Saudi Arabia of dozens of princes and other members of the elite as well as increased tensions between the Gulf Cooperation Council (GCC) and Iran over Yemen and Lebanon (Raper 2017).

On 14 November 2017, the International Energy Agency (IEA), which oversees supply and demand forecasts, expressed doubt that 60 USD was the bottom price for oil; however, IEA analysts acknowledged that geopolitical hazards had become the dominant factor in the market. Since Iraq recaptured Kirkuk from Kurdish forces in October, its oil supplies have sharply declined. These events have added at least 10 USD to the price of oil, and this hazard premium could disappear as quickly as it appeared (IEA 2017).

In addition to geopolitics, two other causes of volatility should be mentioned. Since their collapse below 30 USD in early 2016, oil prices have mostly been affected by intense shale production in the US as well as world reserves set by members of the Organisation of the Petroleum Exporting Countries (OPEC) and independent, non-OPEC producers such as Russia. Bullish oil prices indicate that shale production is declining and that US producers are producing less. If profits are not anticipated, Wall Street provides less finance to the expansion of oil. According to the IEA forecast, by 2025, shale oil will help the US to become a world leader in the production of ‘black gold’. Saudi Arabia will be in second place, and Russia will move to third place (Energy Institute 2018).

Currently, oil is not only an essential natural resource but also a significant instrument of political and global economic influence. Therefore, for competent forex money management, fundamental analyses should consider the state of the oil market and the relationship between the oil and forex markets. A fall in the price of oil affects the US dollar, which is beginning to rise against the euro, the Canadian dollar, the Russian rouble and other currencies. Rajhans and Jain (2015) refer to this as 'oil pressing against the dollar'. Because many other currencies are associated with the dollar, and a change in the price of a natural resource, which affects the dollar, simultaneously affects other instruments, oil must be considered when managing capital in the foreign exchange market (Rajhans & Jain 2015). In particular, the impact of oil on the dollar and the trading process in general is noticeable when the foreign exchange market is in a state of waiting (flat) and there is no pronounced movement in one direction or another. During such uncertainty, a fundamental analysis that considers changes in the price of a natural resource will help predict movement in the foreign exchange market (Rajhans & Jain 2015).

The logical result of the relationship between oil and forex currencies is that oil is a popular tool in trading, and access is provided by almost all forex brokers. Traders trade alleged contracts for difference (CFDs). Trade is conducted for raw materials, both processed and untreated, as well as item futures. Oil from different brokers is designated differently and includes the name of the brand, such as UK oil (Brent) and US oil (WTI). It is necessary to consider this factor, which would seem to be of secondary importance when the main factors demonstrate uncertainty. In this case, the change in the price of oil is an essential guide to understanding the market situation (Gilfillan 2018).

In addition, like any other raw material, oil can be considered a stable investment instrument. The relative stability of this natural resource is explained by its increased importance and consumption, the dynamics of which indicate growth. The dangers of such investments are significantly lower than, for example, investments in securities or currency instruments. Sharp fluctuations are rare for oil, and price stability favourably affects the stock and currency markets. However, political factors should not be overlooked; the current decline in the price of oil is attributable to political rather than economic factors (Rajhans & Jain 2015).

The Crude Oil Volatility Index, released on the Chicago Board Options Exchange, is calculated using the Black–Scholes formula based on the price of 30 days of put and call options for shares in the Exchange Traded Fund (ETF) reserve of the United States Oil Fund. This ETF reserve invests in the future of West Texas petroleum with the closest expiration dates. Therefore, the stock price of the reserve correlate accurately with the price of WTI crude oil. In this case, changes in the volatility index can be used for analysis when trading CFDs for oil of any brand. With a low-level volatility index, the sale of contracts and growth should be considered (Babu & Paul 2014).

3.3.4 Volatility Spillover and COVID-19

Financial markets can be disrupted by events and crises (Claessens & Kose 2013), which may be political (Bashand & Alsaifi 2019; Shanaev & Ghimire 2019) or related to infectious outbreaks such as Ebola virus disease (Ichev & Marinč 2018) or COVID-19 (Al-Awadhi et al. 2020). Ajmi, Arfaoui and Saci (2021) examined the volatility spillover between the US stock market and the commodities market, specifically gold and crude oil, prior to and during the COVID-19 pandemic. Using a multivariate GARCH–BEKK model, the authors examined daily returns volatility for 1 year prior to the World Health

Organisation's (WHO) announcement of the COVID-19 and for the first 7 months of the pandemic (only the peak of COVID-19). They found an increase in volatility spillover across the markets under study, indicating that these markets, particularly the gold market, are better used as diversification techniques rather than hedging tools.

Elgammal, Ahmed and Alshami (2021) revealed bidirectional return and volatility spillovers between the S&P 500 and the gold market and unidirectional volatility spillovers from oil markets to the S&P 500 and gold market. According to their bivariate GARCH model, oil markets appeared to have a significant cross-volatility spillover effect on other markets, which may be explained by the 2020 collapse of oil prices.

Using panel data analysis, Al-Awadhi et al. (2020) examined the relationship between the daily growth in the number of confirmed COVID-19 cases and deaths and daily stock returns in the Chinese market, finding that an increase in both confirmed cases and deaths had a significant negative influence on stock returns across all firms. Jebabli, Kouaissah and Arouri (2021) also studied the COVID-19 phenomenon and volatility spillovers between the energy and stock markets. However, in contrast to earlier reviews, which compared the pre- and post-COVID-19 or pre- and post-GFC periods, the authors compared the COVID-19 and GFC periods, finding that volatility spillover between the energy and stock markets was greater during COVID-19 than it was during the GFC. Jebabli et al. (2021) also noted a shift in spillover patterns between the two crises—during the GFC, volatility transferred from the European stock market to the energy market, whereas during the COVID-19 crisis, the European stock market was a recipient of volatility from the energy markets.

3.4 Effects of Foreign Ownership

Financial liberalisation attracts more foreign investors to local stock markets. In a study based on data from 12 countries, Henry (2000) found an abnormal increase in stock returns following the liberalisation of stock markets. Stock return increases have largely contributed to increases in foreign investments. Evidence shows that foreign institutional investors affect major strategic decisions at the corporate level, in turn influencing market performance. Andriosopoulos and Yang (2015) found that foreign institutional investors increased the likelihood of cross-border mergers and acquisitions in the UK.

Lee and Chung (2018) investigated the links between the price effect of trade, the bid–ask spread and foreign ownership in 20 developing markets, finding that foreign investors reduced trading costs because their presence enhanced competition. Moreover, foreign investor participation in local stock markets is associated with an increase in stock liquidity, which may have positive implications for the development of the stock market.

Rhee and Wang (2009) studied the relationship between foreign ownership and stock market liquidity in Indonesia using a data sample from January 2002 to August 2007, when foreign investors owned more than 70% of the free-float value of the Indonesian equity market. The findings show that a 10% rise in foreign ownership led to a 2% increase in the bid–ask spread. The findings also revealed a 3% decrease in depth and a 4% increase in the price of stocks in the subsequent month. Gul, Kim and Qiu (2010) generated similar findings to those of Rhee and Wang (2009). The authors evaluated the impact of foreign ownership, ownership concentration and audit quality on stock price synchronicity in China and found that foreign ownership was not correlated with price synchronicity. Ferreira et al. (2017) compared the performance of local and foreign institutional investors in 32 stock markets, finding that both local and foreign institutional ownership are positively associated with future returns. Moreover, domestic institutional investors performed better in high-information asymmetrical markets.

More studies are needed to thoroughly understand the key tenets of foreign institutional investment in stock markets. Investigating the largest stock market in MENA and GCC countries will add important empirical evidence to the existing literature. This thesis addresses the effect of stock market liberalisation, specifically foreign institutional investor reforms, on stock market performance.

3.5 Effects of Global Index Reclassification

Previous studies (Griffin & Sanvicente 1982; Norden & Weber 2004) have shown that security rating announcements may affect stock performance. For example, in their pioneering study, Griffin and Sanvicente (1982) explored the reaction of common stock returns to rating changes. They obtained stock price data for the 12 months before and after announcements related to bond rating changes. The results revealed that any decrease in bond ratings was directly passed on to shareholders, highlighting a positive correlation between bond upgrading and return on firm value.

Norden and Weber (2004) analysed the relationship between the stock and credit default swap markets based on the announcements of the top three credit rating agencies from 2000 to 2002. The findings revealed that investors in a selection of stocks listed in 90 markets in Europe and the US anticipated the statements made by the top three firms. However, it was not possible to rule out the impact of previous announcements on both markets. Additionally, the markets greatly reflected the effects of the announcements made by Moody's and S&P.

In the past, several scholars (Abuzayed & AlFayoumi 2017; Burnham et al. 2018; Hacibedel & Bommel 2007; Mendes & Martins 2018) have stressed the importance of investigating the impact of stock market classification announcements on the stock market. Upgrade announcements made through global index agents are expected to trigger capital flow from foreign institutional investors into the stock market, affecting stock market performance, because upgrade decisions are made by a number of active international investors.

In their study on the effect of index inclusions and deletions from MSCI, Hacibedel and Bommel (2006) analysed 531 stock returns from 1996 to 2004. They investigated short-term and long-term price effects and found positive permanent effects when stocks are added to an emerging index and negative permanent effects when stocks are deleted from the index. Prices also reacted more strongly to stock deletions than to stock inclusions in the short term.

Abuzayed and AlFayoumi (2017) examined the effect of the MSCI upgrade of Qatar, Dubai and Abu Dhabi stock exchanges from frontier to emerging markets on returns and volatility. Using sing multivariate BEKK and DCC GARCH framework and found Stock markets responded positively to the reclassification, triggering the entry of foreign institutional investors into the markets. These findings support the price pressure hypothesis but conflict with the free information hypothesis.

Mendes and Martins (2018) divided stock markets into developed, emerging or frontier markets and performed a discriminant analysis using daily data from 40 stock markets provided by Dow Jones. They accurately predicted 10 new stock market reclassifications, with only one stock market misclassified.

Using MSCI data on developed, emerging, frontier and standalone markets, Burnham, Gakidis and Wurgler (2018) investigated the impact of stock market reclassifications on stock returns. They found that stock prices substantially overshoot following an upgrade announcement and decline following a downgrade announcement because the stock market experienced net buying (selling) pressure and positive (negative) alpha for the reclassified stocks.

3.6 Religious Norms and Stock Markets

Several theories emphasise that social norms greatly affect the performance of stock markets. Societies have different definitions of social norms based on their political, moral and religious orientations. Social norm–conforming investments are those in industries that comply with the society's ethics and morals, while social norm–conflicting investments are those in unacceptable industries from the perspective of societal norms (Baker & Nofsinger 2012). Religious principles are an essential determinant of social norms in society. In this thesis, religious principles rather than wider social norms are adopted as a means of classifying stocks. The definition is limited to a pure economic assessment of stock market liberalisation.

Hong and Kacperczyk (2009) compared the performance of 'sin' and 'non-sin' stocks traded in the US. The three 'sin' stocks (alcohol, gaming and tobacco) were based on socially responsible investing criteria in a Christian country. The authors hypothesised that many investors do not wish to purchase the stocks of firms involved in unethical or immoral activities. They found that norm-constrained investors avoid unethical stocks and that social norms greatly affect stock prices and returns. Similarly, based on data from 2004 to 2012, Borgers et al. (2015) found that US-based mutual equity fund managers avoided buying stocks that conflicted with the country's Christian social norms.

Furthermore, previous studies of the stock markets in Islamic societies indicate two general Islamic screening strategies. Al-Awadhi and Dempsey (2017) and Alotaibi et al. (2020) describe the strict Islamic screening strategy as dividing stocks into two categories: Islamic stocks (IFP-conforming) and conventional or non-Islamic stocks (IFP-conflicting). The relaxed Islamic screening strategy divides stocks into three categories: Islamic stocks (IFP-conforming), mix stocks (IFP-accepted by some Muslims traders), and non-Islamic stocks with activities that conflict with Islamic financial principles (IFP-conflicting).

Some recent studies have shown the effect of the strict religious principles in Islamic countries. Under Islamic principles, stocks are divided into IFP-conforming and IFP-conflicting stocks. Most stock market participants in Islamic countries adhere to religious beliefs; thus, they tend to favour Islamic-conforming stocks over Islamic-conflicting stocks. Al-Awadhi and Dempsey (2017) examined Islamic-compliant and Islamic-noncompliant stocks in several Islamic countries. They found that the Islamic-compliant stocks were more liquid, but Islamic-noncompliant stocks paid higher returns as compensation for the higher risk involved in purchasing neglected stocks. Because there is less information about noncompliant stocks, investors must be compensated with higher returns. Similarly, Alhomaidi et al. (2019) compared Islamic and non-Islamic stocks in Saudi Arabia to investigate the impact of Islamic social norms on market segmentation and determine how economic information affects asset prices. They reported a greater integration with macroeconomic variables and a higher systematic turnover for Islamic stocks.

In the context of volatility and market segmentation in Islamic countries, Abduh (2020) made an important contribution to the literature by investigating the volatility of conventional and Islamic indices and examines the impact of the GFC on the volatility of Malaysia stock markets. The study obtained daily data from January 2008 to October 2014 for Bursa Malaysia Kuala Lumpur Composite Index and FTSE Bursa Malaysia Hijrah-Shari‘ah Index. Using GARCH (1,1) model to measure the volatility of the two markets and an Ordinary Least Square Model (OLS) to investigate the effect of the GFC on the volatility. The results show that the Islamic index was less volatile during the crisis compared to the conventional index, and the crisis had a significant impact on the volatility of the conventional index in the short run and the Islamic index in the long run.

On the other hand, Miniaoui et al. (2015) examines the effects of the GFC on the Islamic and conventional indices of the GCC countries. The study used a sample of daily data from 2008-2014 and employed a GARCH (1,1) model to analyse the impact of the GFC on the GCC countries. The results of the study showed mixed outcomes, with the GFC having a significant influence on the Kuwait, Bahrain, and UAE stock indices, but no significant evidence of the GFC on the volatility of the Saudi Arabia, Oman, and Qatar. Moreover, the Islamic stocks indices did not have lower volatility than their conventional stock indices.

Fakhfekh et al. (2016) conducted a comparison of the volatility dynamics of conventional and Islamic banks in the GCC countries, using daily data to the FI-EGARCH (Fractionally Integrated Exponential Generalized Autoregressive Conditional Heteroscedasticity) model to measure volatility persistence. The findings of the study showed that bad news had a stronger effect on volatility than positive news (asymmetric), and that conventional banks were more affected by negative news than Islamic banks. The study also found that volatility was more persistent in conventional banks than in Islamic banks, indicating that Islamic banks are more resilient than conventional banks.

The study suggested that industry rules of Islamic banks could be used to regulate the conventional banking system, noting that Islamic banks in Saudi Arabia tend to provide the most resilient Islamic Bank benchmark model specially in crisis time.

Another study by Albaity and Ahmad (2011) conducted an investigation to explore the behaviour of returns and volatility of three Islamic stock market indices listed in two non-Muslim countries and one Muslim country (DJIMI, FTSEGII, and KLSI) listed in the US, the UK and Malaysia, respectively. Using daily data from January 1999 to October 2007, the GARCH-M model was used to examine whether there were differences in returns, volatility, the leverage effect and volatility spillover among these Islamic indices. The results of the study showed that there was no significant difference in the returns and volatility among the indices. Furthermore, there was no evidence of a leverage effect in KLSE, while DJIMI and FTSEGII indicated significant leverage effect. Lastly, there was a spillover from DJIMI and FTSEGII toward KLSI, but not vice versa.

However, unlike most previous studies, Rejeb and Arfaoui (2019) conducted a study to examine the informational efficiency and volatility of Islamic stock indexes in comparison to conventional stock indexes during the GFC period. Using daily prices of ten Islamic and conventional indices covering the period from January 1996 to January 2016, the study implemented a modified GARCH(1,1) model and included structural breakpoints. The results showed that Islamic stock indexes were more volatile than conventional stock indexes, but also more efficient.

Moreover, growing number of studies provide valuable insights into the volatility spillover within Islamic stocks. They shed light on the long-term effects, magnitude, and speed of volatility spillover during crises such as the GFC, as well as the impact of factors like oil market volatility. The studies also highlight the variations across countries and the correlations between Islamic and conventional stock indices during different market conditions.

The study by Hassan et al. (2020) examined the volatility spillover between conventional and Islamic stock indices, along with the WTI oil market in BRICS countries during the Global Financial Crisis (GFC) period. Using TGARCH and VAR Analysis, the study found that the total volatility spillover between Islamic and conventional stock indices, as well as crude oil, had a long-term effect. Furthermore, the magnitude and speed of the volatility spillover significantly increased during the GFC. The study also revealed that the covariance between Islamic and conventional stock indices was the highest, and it experienced a substantial increase during the GFC.

In the research conducted by Mensi et al. (2021), daily prices of Islamic and conventional bank stock indices for five GCC countries, along with oil and gold prices, were analyzed. Employing DECO-FIGARCH and VAR Analysis, the study discovered significant volatility spillover between Islamic and conventional GCC bank stock indices, as well as the oil and gold markets. This effect was particularly pronounced during periods of the GFC and the 2014-2015 oil price collapse. The study further identified that oil, gold, and conventional bank stock indices of Saudi Arabia, Kuwait, and Qatar acted as net transmitters of volatility, while all the Islamic bank indexes and the conventional bank indexes of UAE and Bahrain were net recipients.

Tanin et al. (2022) examined daily data for 41 Islamic banks and 90 conventional banks to explore the impact of oil market volatility. Using Multivariate GARCH-BEKK, the study found that oil market volatility had a stronger impact on countries that were net exporters of oil compared to net importers. Additionally, the study reported mixed results for Islamic banks, indicating variations across countries. Furthermore, it highlighted that conventional banks within the same country exhibited more significant results in recursive subsamples.

Chazi et al. (2023) focused on the monthly data of the Dow Jones Islamic and conventional stock indices from January 1996 to May 2022. Utilising GARCH (1,1) and DCC-GARCH models, the study revealed that the volatility of Islamic and conventional stock indices was similar during normal times but defer during crises. The findings suggested that the decoupling between Islamic and conventional indices was specific to crisis periods. Moreover, the study noted substantial correlations between Islamic and conventional stock indices during normal situations, and similar mixed results were observed during the GFC and COVID-19 time.

3.7 Financial Reform and Saudi Stock Market

Saudi Arabia's capital market authorisation (CMA) has made reforms to implement a liberalisation strategy since 2015. Specifically, allowing qualified foreign institutional investors (QFIIs) to invest in its markets and reclassifying the Saudi stock market as an emerging market are two of the most important events for global indices (FTSE Russell, 2018).

Previous studies indicates that QFIIs are superior at investing comparing to individual traders, which affects in higher stock returns instead of causing price bubble (Opie & Zhang 2013; Choi, Jin, & Yan 2013). Accordingly, the goal of inviting the QFIIs is achieving more investors’ base diversification advantages, enhances stock market performance in term of increase return, and reducing systemic risk (Chen et al. 2013; Vo, 2015; Balakrishnan et al. 2019; Al-Faryan & Dockery 2020). Further, According to a study by Almutiri (2020), the QFIIs participation (buying and selling) in Saudi stock market enhances the performance of the overall index of the market. On the other side, globalisation may also cause these markets to be more susceptible to global risk factors, which can results in high sensitivity to global crises (Mobarek & Mollah 2016).

The Saudi stock exchange is vulnerable to market segmentation based on social norms, which is a vital issue that needs to addressed. Social norms, existing in Islamic societies in particular, are significantly driven by religion and influence investors' behaviour in these societies (Kumar 2009; Kumar & Page 2014). As a result, Islamic social norms segment the stock market into Islamic stocks and conventional (non-Islamic) stocks (Alawadhi et al. 2016, Alawadhi 2019). Whereas participants in an Islamic society's stock market prefer to avoid buying financial assets that conflict with Islamic social norms, which leads to an increased demand and liquidity for stocks conforming to Islamic social norms for investment (Gregoriou et al. 2016; Alawadhi & Dempsey 2017; and Alhomaidi et al. 2018). On the other hand, conventional market segments, which do not comply with religious (Islamic) beliefs, may diminish the capacity to attract capital from faith-driven investors. It would increase the costs of accessing capital, and increase liquidity risk (Alawadhi et al. 2016; Kim et al. 2018); and more exposed to the marker fear (Risk) than Islamic stocks which make it more volatile (Karim, Kawsar, Ariff, & Masih 2022).[8]

3.7.1 Risk Adjusted Performance

Previous studies have discussed the analysis of return and risk in evaluating investments and identify stocks that have a tendency to outperform the market. To gain insight into the risk-adjusted performance of stocks, many studies have presented their analysis of the risk-adjusted performance metrics, such as Sharpe ratio (SR), Treynor ratio (TR), value at risk (VaR), and Conditional value at risk (CVaR). Standard deviation can help measure the volatility of returns and calculate the Sharpe ratio, whereas TR can provide insight

[8] More studies about stock market segmentation base in social norms is reviewed later in this chapter.

into assessing excess return per risk (Beta) (Bodie et al. 2010). Nevertheless, Beta here only measures systematic risk, not global risk (standard deviation).[9]

Additionally, volatility behaviour studies have been implemented to better understand how a stock's returns behave in both up and down markets. Taking into account both risk-adjusted performance metrics and volatility behaviour studies, investors can make more informed decisions when selecting an investment. This is important for investors as it allows them to assess the risk-adjusted performance of an asset and make decisions that may lead to improved returns.

As Alqadhib et al. (2022) examines the impact of COVID-19 on the risk-adjusted performance of mutual funds in Saudi Arabia, it is rational for investors to consider the risk-adjusted performance during other periods, based on new policies and events such as the new era of Saudi financial reforms which was introduced in 2015. The liberalisation of the Saudi economy might have changed many aspects of the stock markets.

According to Ashraf (2013), Islamic stocks outperform conventional stocks in terms of risk-adjusted performance, particularly during times of crisis. Therefore, it is important to investigate the Saudi stock market segments based on the Islamic social norms performance have changed due to liberalisation. If this is correct, and the stock market shows any changes in performance, then it is expected there will be a significant correlation between return and risk (volatility) relevant to the policy of liberalisation of the Saudi stock market segments based on the Islamic social norms. Thus, the study first hypothesis is:

[9] More details about risk-adjusted performance in the next chapter.

Hypothesis 1 (H1): financial reforms introduced in 2015 to the Saudi stock market have changed the performance of the Saudi (Islamic / Mixed / Non-Islamic) stock indices.

3.7.2 Financial Reform and Volatility Pattern

As mid of 2015, the Saudi stock market (as leading Islamic country) experienced high volatility (Kalyanaraman 2014; Lamouchi 2020). According to previous studies, high volatility in the Saudi market is caused by various features, including a weak form of stock price inefficiency (Butler & Malaikah 1992; Al-Ajmi & Kim 2012; Budd 2012; Syed & Bajwa 2018); association with a highly volatile commodity (oil) market (Almohaimeed & Harrathi 2013; Arouri et al. 2011; Arouri & Rault 2012; Hammoudeh & Aleisa 2004; Zarour 2006); and substantial individual participation, which is more likely to be noise traders in stock buying and selling (Rahman, Chowdhury, & Sadique 2015; Deloitte 2010; Lerner, Leamon, & Dew 2017). Also, the Saudi stock market is labled to have large blockholder ownership, particularly by the Saudi government (Tadawul 2020). In addition, the Saudi stock market is considered to be dominated by large blockholder ownership, particularly by the Saudi government (Tadawul 2020). Moreover, the influence of Islamic social norms, which segment the stock market, may cause differences in volatility patterns based on the market segment (Canepa & Ibnrubbian 2014; Alhomaidi, Hassan, Zirek, & Alhassan 2018; Alhomaidi, Hassan, Hippler, & Mamun 2019).

After establishing the modernising (liberalisation) reforms, the Saudi stock market has already seen some progress. For instance, statistics show that the QFIIs number in the Saudi stock market have increased to become more than 1,500 as of October 2019 (Tadawul 2020). This QFIIs participation enhances the performance of the Saudi stock market (Almutiri 2020); inefficiencies of stock market changed as time progressed (Shawer & Al-Ajlouni 2018).

In terms of return and volatility, Sharif (2019) has investigated the reform impact of the "open the market to foreigners" policy on the overall index and found a significant decrease in return and an increase in positive abnormal returns post-reform. This mixed evidence suggests that foreign participation increases the volatility of Tadawul. However, there is a need to further investigate the impact of the reforms on the Saudi stock exchange, particularly in terms of return and volatility behaviour based on Islamic social norms. Therefore, identifying the impact of the reform on market segments based on Islamic social norms may lead to a finding of whether volatility pattern varies between conventional and Islamic stocks.

A study by Alghfais (2018) conducted analysis on the daily returns of the Tadawul All-Share Index (TASI) to forecast the volatility using the simple ARCH, GARCH, EGARCH, and TGARCH models. The study finds that the asymmetrical EGARCH (1,1) model performs better than all other models in estimating the returns volatility of Saudi all share index in the short term. Also, according to Alghfais (2018), the symmetric GARCH (1,1) model outperforms all other GARCH family types in modelling the returns volatility of Saudi all shares index in the long term. However, Alghfais (2018) has not clearly distinguished the reform period in his study sample, which may not help to identify the change in volatility pattern caused by the new phase of stock market reform.

Therefore, in the context of the Saudi stock market, studies of volatility patterns between three groups of stocks according to Islamic religious principles and between the overall Saudi stock market are vital. This inclusion will not only enhance the accuracy of volatility estimations but also enable the capture of changes in volatility pattern corresponding to the Saudi liberalisation reforms. Thus, the second hypothesis is:

Hypothesis 2 (H2): the volatility pattern for the Saudi stock market indices have changed due to the liberalisation of the Saudi market in 2015.

3.7.3 Volatility Spillover Effects Related to Saudi Arabia

A major aim of stock market liberalisation in Saudi Arabia is to bring about a more global and modernised market, potentially attracting and facilitating foreign direct investments into the Saudi economy. This is expected to not only reduce Saudi dependence on oil income but also increase its integration with global markets. Liberalisation initiatives have further implications on spillover effect of returns volatility among Saudi stock market and other financial markets. (Zhou et al. 2012).

Over the last few decades, scholars have investigated the issue of volatility spillover between different financial markets in different countries, with many focusing on the flow of information from one financial market to another. For instance, using a VAR–GARCH approach, Arouri, Lahiani and Nguyen (2011) captured the volatility spillover between the oil market and stock markets in the GCC based on daily data from 2005 to 2010. Their results were supported by Almohaimeed and Harrathi (2013), who implemented a VAR–BEKK specification on daily returns for sectors and the overall Saudi index from 2009 to 2012 and identified a positive volatility transmission between the oil market and the Saudi stock index.

Awartani, Maghyereh and AlShiab (2013) investigated returns volatility spillover between the US S&P 500 and GCC equity markets, including the Saudi market (TASI) but found no significant volatility spillover between the US and Saudi markets. However, they identified a new information transmission pattern reflecting a strengthened association between the US and Saudi stock markets during the GFC. Additionally, Alotaibi and Mishra (2014) investigated returns volatility spillover from a regional Saudi market and the international US market for the remaining GCC stock markets (United Arab Emirates, Bahrain, Kuwait, Oman and Qatar). Implementing bivariate GARCH models (BEKK, CCC and DCC), the authors found a significant transmission of volatility from Saudi and US markets to the GCC markets.

Erdoğan et al. (2020) used weekly crude oil prices and stock market returns from 2001 to 2018 in Saudi Arabia to quantify volatility spillover between the oil and stock markets. They applied an APARCH model along with causality-in-mean and causality-in-variance tests to capture leverage effects and volatility transmission. The authors found a bidirectional causality relationship between stock returns and oil prices and strongly suggested that crude oil be used as a hedging strategy in portfolio allocation decisions.

Similarly, Ziadat and Alkhouri (2022) measure the volatility spillover patterns between the GCC stock indexes over a sixteen year period (2004-2020). They employ Diebold and Yilmaz's (2009) method to quantify the volatility spillover. Their research results demonstrate an increase in spillover during crisis periods such as the GFC, oil price shocks, and the COVID-19 pandemic. Additionally, they find no significant changes in the directional patterns of volatility during the pandemic.

Between July 2004 and March 2021, Yousaf et al. (2022) explored asymmetrical volatility spillover and dynamic correlations between the GCC stock markets and five global markets (Islamic equity, energy, gold, bonds, and real estate). The authors used a bivariate VAR-Asymmetric-BEKK-GARCH model to analyse the data, and considered the impacts of the GFC and the COVID-19 pandemic. The results showed that there were significant spillover in both returns and volatility between the GCC markets and the global factors, which became more pronounced during times of crisis. Furthermore, the time-varying correlations demonstrated that gold market served as a hedging and safe option for the majority of GCC stock markets throughout all sample periods. However, the findings for bonds, oil, Islamic equities, and real estate varied across markets and sample periods.

While some studies have investigated volatility spillover in the MENA context, further research is needed. The literature distinguishing between Islamic and non-Islamic stocks is lacking. Most researchers addressing Islamic principles have used strict screening criteria to categorise stocks, but no study to date has used more relaxed Islamic screening criteria. This thesis extends the existing literature by proposing an alternative, more relaxed categorisation of stocks and ranking stock performance according to Islamic principles.

In the context of the Saudi stock market, studies of volatility spillover between three groups of stocks according to Islamic religious principles and between the overall Saudi stock market and other financial markets such as the oil or global stock markets are crucial. This inclusion will not only enhance the accuracy of volatility estimations but also enable the capture of change in spillover effect of volatility between the Saudi stock indices and the oil or US stock markets corresponding to liberalisation reforms. Thus, the third hypothesis is:

Hypothesis 3 (H3): the volatility transmissions from global markets (brent, WTI, & S&P 500) to Saudi stock market indices have change after the liberalisation.

3.8 Portfolio Management

Markowitz (1952) proposed the modern portfolio theory as a portfolio management framework to reduce risk through diversification and stock correlations. Optimal portfolio management is based on balancing risk and return. Modern portfolio theory considers the movement of each asset relative to other assets in a portfolio to increase overall returns.

According to Koumou (2020), the concepts of the law of large numbers, correlation, capital asset pricing model, and risk contribution are fundamental to understanding diversification in portfolio theory. These four principles serve as the foundational pillars of both modern portfolio theory and asset pricing theories, playing a crucial role in grasping the essence of diversification.

Constantinides and Malliaris (1995) were the first to theorise the separation of asset allocation decisions and interest rate determination from portfolio selection. They argued that asset allocation and interest rate determination are based on different approaches, despite overlapping in several aspects. Asset allocation utilises deterministic calculus to maximise utility with monetary restrictions, whereas portfolio selection aids decision-making in uncertain conditions. Therefore, asset allocation and interest rate determination represent two distinct aspects.

Another important portfolio management theory is the capital asset pricing model (CAPM), which prescribes asset options by assuming that only the first two moments of return sequences are relevant. It further assumes that investors consider a single-period time frame, prefer lower-risk portfolios and will readily dispose of their stocks and short-sell their assets. Moreover, the model ignores transaction expenses. CAPM is a vital element of portfolio management theory. Fama (1976) and Roll (1977) proposed that the use of the CAPM is similar to the mean-variance analysis of the market. Accordingly, it requires the inclusion of all market stocks. Moreover, a proxy does not work for CAPM for several reasons. The proxy may be mean-variance efficient, while the market may be inefficient, and vice versa. Therefore, CAPM is a vital element of the model but requires the inclusion of all stocks for efficiency reasons.

In addition, multi-index models are essential for portfolio management and are the foundation of arbitrage pricing theory. Elton and Gruber (1997) observed that these models are useful for measuring index betas and variances. Portfolio managers utilise them to conduct sensitivity analyses. They measure the influence of various external factors on the performance of stocks, which aids them in forecasting index changes. Therefore, multi-index models make up the foundation of arbitrage pricing theory by helping in sensitivity analyses.

Further, international diversification is fundamental to risk reduction strategies. Several studies shed light on the effectiveness of this technique. For instance, Solnik (1974) found that global diversification reduces the variance of a portfolio by half. Other studies show similar results. In addition, international diversification is relatively easier today because of financial mobility and advanced communication technologies (Agénor 2001; Issing 2000). The resultant globalisation catalysed the amalgamation of economic and financial networks, supporting diversification (Beine et al. 2010). Therefore, given technological advancements, international diversification is relatively easier and effectively reduces risk.

Uludag and Khurshid (2019) conducted a study on the optimal weights and hedge ratios to mitigate risk from the Chinese stock market to the E7 and G7 stock markets. The study used daily volatility data from 1995 through 2015 and found that investors should allocate more assets from G7 countries than E7 countries for their portfolios.

Nevertheless, globalisation and international diversification come with certain disadvantages, such as the challenges associated with investing in emerging markets as part of a global diversification strategy (Kearney & Lucy 2004). Beine et al. (2010) refer to this as a connectivity disadvantage. They propose that benefiting from globalisation could be problematic during an economic crisis because of tail dependence.

More recent research on portfolio management by Jebabli, Kouaissah, and Arouri (2022) suggests that the optimal weights are affected by structural changes associated with the Global Financial Crisis of 2008 and the Covid-19 pandemic crises. Additionally, their study found that a mixed portfolio of crude oil or natural gas stocks can provide more effective hedging tools, depending on the status of these markets.

As an alternative to emerging and developed markets, frontier markets are an attractive investment option, offering significant growth and profit opportunities for investors. Girard and Sinha (2008) investigated 360 stocks of 19 frontier markets for a prolonged period and found significantly high returns compared with emerging and developed markets. However, frontier markets carry high risks. Nevertheless, many investors understand the concept of risk–reward and are willing to accept higher risks in return for greater yields. Frontier markets are perceived as a model for risk–return. In addition, identifying the correct frontier markets is critical for investor confidence. Therefore, frontier markets are an attractive alternative to traditional investment markets, offering high growth, profit and risk.

However, frontier markets have several disadvantages. Their liquidity is considerably lower than that of developed markets. Marshall et al. (2015) revealed that the average spread in frontier markets is two and half times higher than that in US markets, signifying liquidity issues. Moreover, they found a positive relationship between transaction costs and margins. Further research reveals that Gulf nations have the lowest transaction expenses. Qatar, in particular, has the lowest spread and transaction costs (Marshall et al.

2015). In addition, the authors observed that benefiting from frontier diversification requires quarterly stock rebalancing. Similarly, Berger et al. (2013) found frontier markets to be idiosyncratic. Therefore, frontier markets carry several disadvantages, including short liquidity, low spreads and periodic rebalancing of stocks.

Gulf stock markets show unidirectional changes. Neaime (2006) studied several Arabic markets over a prolonged period and observed that the Bahraini market created unidirectional mean and variance changes in the Saudi and Kuwaiti economies. Further, their research revealed Gulf stock markets as attractive diversification options. Hammoudah and Choi (2006) observed a negative correlation between international and Gulf stocks. They noticed that compared with global events, local factors significantly affected Gulf markets. Therefore, Gulf markets offer viable global diversification opportunities.

Several other researchers have studied Gulf markets. Abraham et al. (2001) investigated the efficient allocation of securities in the Bahraini, Saudi and US markets. They reported higher yields and lower variances for portfolios diversified in US and Gulf markets. Similarly, Khalifa et al. (2014) found attractive gains from diversifying between the WTI, US, MSCI World Index and Gulf markets. However, they revealed an increasing sensitivity of stocks to international markets. Nevertheless, Balli et al. (2013) found a decreasing sensitivity of stocks to international markets. Thus, Balcilar et al. (2015) recommend diversifying global portfolios with Gulf assets. Therefore, several researchers have corroborated previous studies of the benefits of diversification in Gulf economies, albeit with conflicting sensitivity results.

Moreover, researchers have studied GCC markets by sector. Hammoudeh et al. (2009) applied a VAR–GARCH model to measure the riskiness of the service, financial and manufacturing sectors of various Gulf markets. They found highly significant idiosyncratic variations compared with previous shocks and that risk and variations spread across sectors in the Gulf markets. Moreover, their sector-based evaluation highlighted the potential of the financial sectors of Qatar, Saudi Arabia and the United Arab Emirates and the industrial sector of Kuwait. Therefore, this sector-based study of Gulf economies revealed significant idiosyncratic variations, intersectoral risk and high-potential areas.

Researchers have also investigated Gulf oil linkages. Hammoudeh and Eleisa (2004) analysed the impact of oil prices on GCC markets, revealing a weak correlation between the two. However, later research generated conflicting results. For instance, Jouini and Harrathi (2014) and Mohanty et al. (2011) observed a strong positive correlation between the oil and industrial markets in the GCC. Thus, investors can benefit by diversifying their stocks in both oil-importing and Gulf nations (Arouri & Rault 2010). Therefore, the findings on the impact of oil prices on GCC countries are conflicting.

Tien and Hung (2022) found that fluctuations in oil prices have a statistically significant effect on stock markets in the long run, which is useful for investors to consider in their hedging strategies. The study also indicates that oil prices have a noteworthy impact on GCC stock markets in the short and medium term.

According to Yousaf et al. (2022), gold is effective as both a hedging commodity and a safe haven against most GCC stock markets, regardless of the sample period. However, the study found that the effectiveness of bonds, oil, Islamic stocks, and real estate assets as hedges against GCC stocks varies across different markets and sample periods.

Furthermore, as Hung (2021) suggests, GCC countries offer appealing opportunities for international diversification due to their recent liberalisation policies, which may have a connection with the global economy. For instance, Mimouni et al. (2016) studied the impact of oil prices on GCC nations, revealing that oil proceeds make up a major proportion of wealth in Arab economies. However, rising oil prices negatively affect oil-importing countries because they increase costs. Moreover, the authors found striking correlations among the Gulf countries—their pairwise correlations were low and stable compared with the high and unstable international trends. Accordingly, Gulf markets are desirable destinations for international diversification. Similarly, Hammoudeh and Choi (2007) found that Gulf markets are weakly correlated with international businesses compared with other oil-exporting countries such as Mexico. Therefore, GCC countries offer excellent diversification opportunities because of their strong correlation with local factors and weak international market relationships.

Therefore, If the previous study hypotheses are proven, the fourth hypothesis of this study is to investigate the implications of any shift in stock market performance, volatility pattern, and spillover on portfolio management. If this is proven to be significant, it could reveal valuable insights. Thus, the fourth hypothesis is:

Hypothesis 4 (H4): The financial reforms have affected the investors behaviour in selecting optimal weight for their investment portfolio consist of three groups of Saudi stocks.

3.9 Summary of Identified Literature Gaps

This chapter presented the background literature on which this thesis is based and clarified the main concepts employed for the research questions and developed hypotheses. Although the relevant literature is extensive and includes work from several overlapping but related articles, this chapter has identified significant gaps in knowledge, highlighting the relevance of this thesis. Along with identifying gaps in the literature, a key aim of this thesis is to develop an understanding of the return and volatility behaviour mechanisms in emerging Islamic stock markets and global markets covering major policies and event periods such as liberalisation reforms. Therefore, the study developed and link the research hypotheses with the identified gaps in literatures as follow;

First, H1 is developed to empirically investigate the response to the liberalisation reforms on the risk-adjusted performance of Saudi stock market segments based on the Islamic social norms. Most studies on the Saudi stock market have focused on the overall market performance, with several investigating the relationship between the stock market performance and major events such as the Global Financial Crisis and COVID-19. However, there is a lack of research linking the stock market segmentations theory to some major events such as the liberalising and modernising of the local stock market in an Islamic society like Saudi Arabia. To the researcher's knowledge, no research has yet focused on the impact of liberalisation reform on the performance of three market segments (Islamic, mixed and non-Islamic) based on Islamic social norms, particularly in the largest Islamic stock market in the MENA.

Similarly, H2 is developed to empirically investigate the response to the liberalisation reforms on the return and volatility pattern of Saudi stock market segments based on the Islamic social norms. Most studies on the Saudi stock market have focused on estimating the volatility of the overall market or conducting sectoral analysis, with several investigating the relationship between the stock market volatility and major events such as the GFC, the Arab Spring and COVID-19. Further, there is limited works of volatility dynamics, mostly focusing on symmetric and asymmetrical GARCH modelling. To the researcher's knowledge, no known study has estimated the volatility persistence through the half-life perspective obtained from three different univariate GARCH frameworks in the context of Islamic social norm segmentations in Saudi Arabia. Thus, there is a lack of research identifying the return and volatility pattern, including volatility persistence and half-life, on Islamic stock market segmentations theory and response to the liberalising and modernising of the local stock market in an Islamic society like Saudi Arabia.

Third, H3 is obtained to empirically investigate the impact of the liberalisation reforms on the return and volatility spillover between three global markets (Brent, WTI, and S&P 500) and Saudi stock market segments in accordance with Islamic social norms. Many works have investigated the spillover of volatility between overall Saudi stock market and different sectors or between some regional markets in the context of MENA and GCC, or even with global markets like oil market or other developed stock markets like US stock market. Furthermore, most of previous literatures have used only one statistical technique to capture the direction and size of the spillover of volatility in these investigations. However, identifying the spillover of global markets volatility and Saudi stock market volatility using a combination of univariate GARCH, cross-correlation function, and multivariate GARCH approach have not been used in one investigation, especially in the context of the volatility spillover between Brent, WTI, and S&P 500 and three different segments of Saudi stock market categorised by Islamic social norms using multiple timeframes to investigate liberalisation reforms of the Saudi stock exchange.

Finally, H4 is constructed to extend the investigation of the impact of the liberalisation reforms on the return and volatility spillover between three global markets (Brent, WTI, and S&P 500) and Saudi stock market segments in accordance with Islamic social norms by conducting an analysis of portfolio implications (Optimal portfolio weights and hedge ratio). Similar to the previous literature gap, this study found an opportunity to broaden the gap to explore the portfolio implications of the global markets (Brent, WTI, and S&P

500) volatility spillover and three stock market segments to address the Islamic social norms in the context of comparison of the liberalisation reform period and more restrictions period. Thus, the study aims to provide empirical evidence that helps policymakers assess their reforms and managers mitigate their portfolio risk.

Chapter 4 outlines the structure of the thesis and research methodology.

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CHAPTER 4: METHODOLOGICAL FRAMEWORK

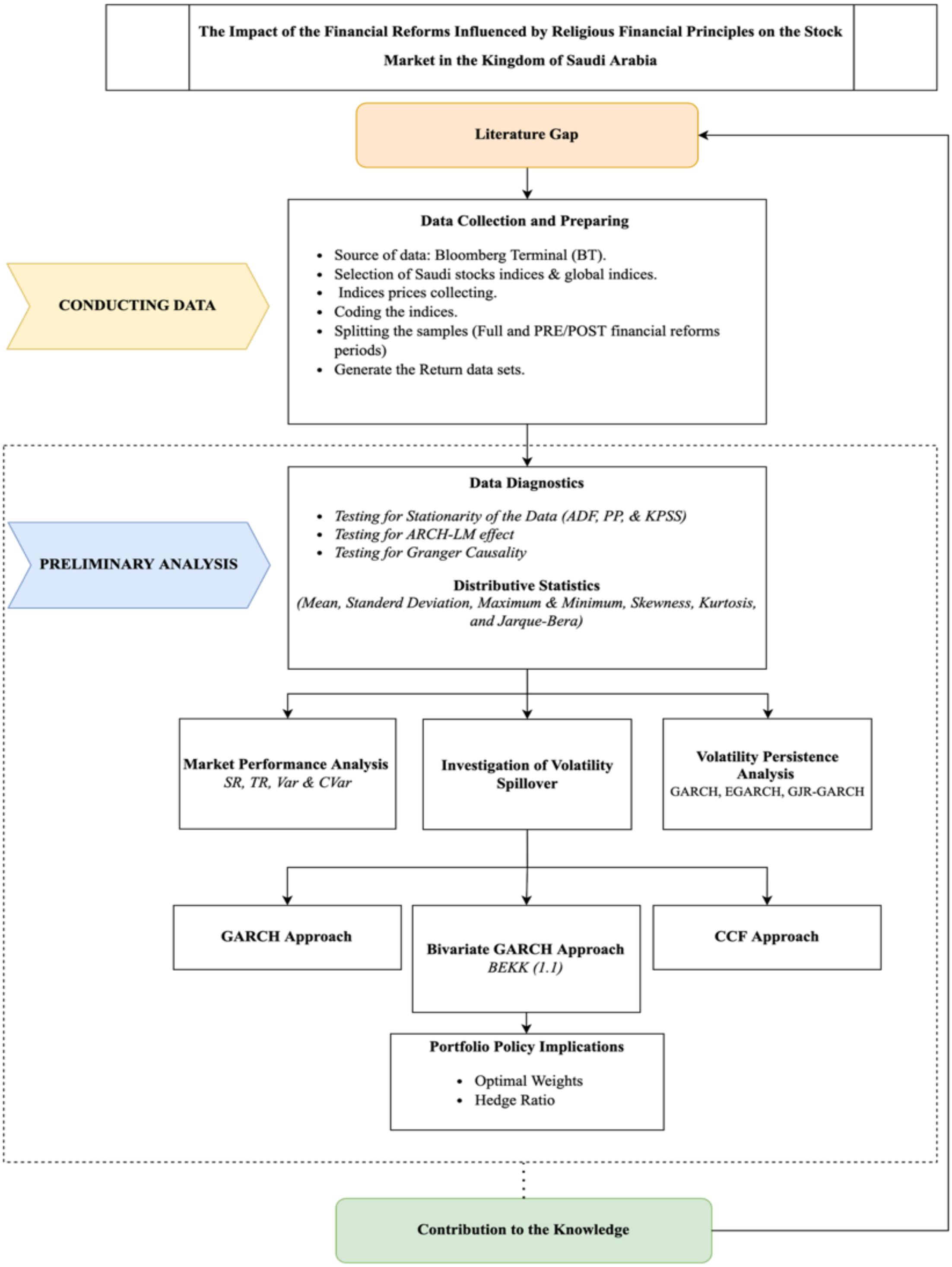
4.1 Introduction

This chapter highlights the methodology employed to address the research questions that were outlined in Chapter 1 and is organised as follows. The methodological framework is presented in Section 4.2. Section 4.3 contains the data-description section, which discusses the source of the data and the sample selection, which includes the market indicators and timeframe. Section 4.4 identifies the measurement of the returns indices. Next, in Section 4.5, the measurement of volatility is described. Section 4.6 identifies the descriptive statistics as the first preliminary analysis section in this study. Then, Section 4.7 introduces the Saudi stock market indices (risk-adjusted) performance analysis, which includes an implementation of the Sharpe ratio (SR), Treynor ratio (TR), Value at Risk (VaR) and Conditional Value at Risk (CVaR) as measurement methods. Then, Section 4.8 identifies the statistical methods employed to test the stationarity of the study data by using the augmented Dickey–Fuller (ADF), Philips–Perron (PP) and Kwiatkowski, Phillips, Schmidt and Shin (KPSS) unit root tests. Section 4.9 discusses the test for multicollinearity between the study's relative indices. Section 4.10 illustrates the implementation of the Granger causality test. Section 4.11 introduces the main statistical models used in this study. Then, Section 4.12 describes the ARCH-LM test. Section 4.74.94.104.124.13 explains the volatility persistence analysis conducted using various types of univariate GARCH models, such as GARCH (1,1), Exponential Generalised Autoregressive Conditional Heteroscedasticity (EGARCH) (1,1) and GJR-GARCH (1,1). Then, Section 4.14 introduces the way that this study tests for the spillover of volatility between global markets and the Saudi stock market. Further, the portfolio implications, including optimal weights and hedge ratio methods, are described in Section 4.15. Finally, the chapter is concluded in Section 4.16.

4.2 Methodological Framework

This study shows the conceptual model to simplify the study's conceptual framework (see Figure 4.1). According to the previous dissections, the methodological framework employs appropriate methods, statistical instruments and processes to objectively answer the questions in Chapter 1. Thus, the methodological framework, including the detailed stages and steps, is illustrated as follows:

Figure 4.1: Methodological framework that illustrates the study's econometrical methods and analyses processes



Notes: Refer to the List of Abbreviations for more clarification.

4.3 Data Description

This study investigates the impact of the liberalising stock market reforms in Saudi Arabia by (1) measuring the risk-adjusted performance, (2) quantifying the persistence of volatility and (3) capturing the returns and volatility spillover from global markets to stock indices as categorised by Islamic financial principles (IFPs). Therefore, to construct the methodological framework, the study must first identify the key components (data) of the employed models for the purpose of finding answers to the research questions that were posed in earlier chapters. It is essential to ensure that proper data sources work together with the adapted econometrics models to properly approach the purpose of this study. In addition, it is necessary to emphasise the criteria that drives the selection of data to be effectively incorporated into the relative models.

4.3.1 Data Sources

Secondary data are collected from the Bloomberg Terminal (BT) database. The BT is an official information provider of Saudi stock market data.[10] Daily historical market data for Brent crude oil and West Texas Intermediate (WTI) crude oil prices are used as proxies for oil prices, the S&P 500 index as a proxy for a global index and the five local stocks indices as proxies for the Saudi stock market. The data covers a period of approximately 12 years (from 4 January 2010 to 29 June 2021). These data are appropriate for the study design that is selected, as is discussed in the data-selection section.

To establish the analyses of a volatility spillover between the external global oil commodity market (Brent crude oil and West Texas oil), the international stock market

[10] See the information providers' directory at https://www.tadawul.com.sa

(S&P 500) and five Saudi stock indices, three stock indices groups—from an IFP perspective (Ideal Ratings Saudi Islamic Index, S&P Saudi Arabia Shariah Index and MSCI Saudi Arabia Domestic Islamic Index–Islamic stocks indices), Tadawul All Share Index (containing a mix of Islamic and non-Islamic stocks) and S&P Saudi Arabia Domestic Index (Conventional Index)—are compiled and daily stock indices prices are collected from the BT (see Table 4.1).

Table 4.1: Selected indices and categorisations

Objective	Categories	Proxy	CODE
Local Indicators	Islamic Stocks Indices	Ideal Ratings Saudi Islamic Index	IS1
		S&P Saudi Arabia Shariah Index	IS2
		MSCI Saudi Arabia Domestic Islamic Index	IS3
	Mixed Stocks Index	Tadawul All Share Index	MS
	Non-Islamic Stocks Index	S&P Saudi Arabia Domestic Index	CS
External Indicators	Oil Prices	Brent Crude Oil	Brent
		West Texas Crude Oil	WTI
	USA Stock Market Index	US Equity Market	S&P 500

Note: This table is structured by the researcher to illustrate and to simplify the categories of the variables that are being investigated.

Given that the equity and commodity indices for selected countries (Saudi Arabia and the United States) are retrieved from the BT, the daily opening and closing prices are collected for the full sample period (from 4 January 2010 to 29 June 2021) to investigate the return and volatility spillover across the study indices before and after the introduction of financial reforms (6 May 2015) in Saudi Arabia (see Table 4.2).

Table 4.2: Schedule of announcements about Saudi stock market reforms

Objective	Reforms	Before Announcement	After Announcement
Foreign Institutional Investors	Launching QFII Program	January 2010 to June 2015	May 2015 to June 2021
	Increasing QFII Ownership Limit	January 2010 to September 2016	September 2016 to June 2020
Reclassification of Saudi Stock Market	FTSE Russell	January 2010 to March 2018	March 2018 to June 2020
	MSCI	January 2010 to June 2018	June 2018 to June 2020

	S&P	January 2010 to July 2018	July 2018 to June 2020

Therefore, it is rational to consider the geographical time zones within the local and global indices in empirical studies. Table 4.3 compares the financial markets of Saudi Arabia with those in the United States in local time and the corresponding Greenwich Mean Time (GMT).

Table 4.3: Time zone and trading hours for Saudi stock market, United States stock market and oil market

Country	Market	Local Time	Greenwich Time
Saudi Arabia	Tadawul	10:00–15:00	07:00–12:00
United States	S&P 500	09:30–16:00	13:30–20:00
United States	Brent Crude Oil	18:00–17:00	22:00–21:00
United States	West Texas Intermediate	18:00–17:00	22:00–21:00

Source: Time zones are obtained from www.greenwichmeantime.com. While the trading times are obtained from the exchange trading hours given in the Bloomberg database in GMT.

From the comparison of the time periods, Table 4.3 demonstrates that all the markets in Saudi Arabia open and close before the markets in the United States. Thus, using data from the same day in the analysis for this study is inefficient, particularly given that this study attempted to capture the impact of global (United States) indicators on the domestic (Saudi Arabia) market and not in the other direction. According to Aityan et al. (2010), including the 'previous day' data (lag) instead of the 'same-day' data in different-zone market analyses is statistically significant. Alternatively, this study considers data from the previous day's indices for markets in the United States and same-day data for the indices in Saudi Arabia.

4.3.2 Data Selection

This section highlights the sample-selection criteria of this study to provide the maximum number of data observations and indices possible to obtain more reliable evidence as is available to answer the research questions. The thesis is about the Saudi financial reforms and its stock market and the influence of IFPs. Therefore, the stock indices that are established for this purpose are obtained from the BT. Any IFP-categorised stock index that is authorised by the Saudi Capital Market Authority (CMA) and the period from 2010 to 2021 (consider pre-reform and post-reform periods) is within the scope of this study. Accordingly, 10 Saudi stock indices and three global indices (Brent, WTI and S&P 500) are identified as follows:

Table 4.4: List of Saudi stock indices based on IFPs

	Index	BT Code	Available Period
1	The IdealRatings Saudi Islamic Index	IRTGSRPR Index	(4 January 2010–29 June 2021)
2	Dow Jones Islamic Market Saudi Arabia Index	DJIMSAUP Index	(18 March 2019–29 June 2021)
3	The S&P Saudi Arabia Domestic Index	SPDSALT Index	(01 December 2008–29 June 2021)
4	S&P Saudi Arabia Shariah Index	SPSHSART Index	(01 December 2008–29 June 2021)
5	MSCI Saudi Arabia Domestic Islamic Index	MISAD Index	(31 August 2007–29 June 2021)
6	Saudi Arabia Dow	SADOWD Index	(18 March 2019–29 June 2021)
7	The MSCI Saudi Arabia Index	MXSA Index	(29 August 2014–29 June 2021)
8	Tadawul All Share Index	SASEIDX Index	(03 January 2000–29 June 2021)
9	Saudi Banks Sector Index	SASETBNI Index	(04 January 2016–29 June 2021)
10	Franklin FTSE Saudi Arabia	FLSA US Equity	(11 October 2018–29 June 2021)
11	S&P 500 Index	SPX Index	(03 January 2000–29 June 2021)
12	Brent Crude Oil	CO1 Comdty	(03 January 2000–29 June 2021)
13	West Texas Intermediate	CL1 Comdty	(03 January 2000–29 June 2021)

Note: The above indices are obtained from the BT on 29 June 2021.

To include as many indices as possible in this study, any index created before January 1 2010 is included in the sample; otherwise, it is omitted. One of the reasons for choosing this date as a benchmark is to avoid any issues that could arise from the global financial crisis (GFC) in 2008 and the recent Russia and Ukraine War in 2022. In addition, the specified period covers the financial-reform phase, which began in mid-2015. Moreover, it is possible to divide the study sample into pre-reform and post-reform periods.

Even though the primary focus of this thesis is the financial changes to the Saudi Arabian stock market, the coronavirus (COVID-19) period is also examined. It is essential to account for this period in the studies by incorporating a subperiod analysis section. This phase extends the content of this research and provides more empirical evidence about the effect of the announcement about financial changes on the Saudi market by advancing the analysis by splitting the post-reform sample into two subperiods (one for the post-reform and pre-Covid period and the other for the post-Covid period).

4.4 Measurement of Returns

This section describes the measurement of returns, which is the first market-performance indicator in this study. The daily returns for the five Saudi equity (stocks) indices, in addition to three global indices, help to illustrate the overall growth of the market and the past developments in stock market performance and to depict the changes in the Saudi stock market.

To calculate the returns of the Saudi stock market, index prices are needed to generate new data sets (returns). First, the index prices are for the full sample period. The sample is then split to consider the two periods before and after the financial reforms, which started in May 2015. The two sets of returns should include current and past stock return data from before the financial reforms announcements. The other two sets should include data from the post-announcement period. Then, the results are compared. The returns equations (R_t) are:

$$R_t = [\ln(P_t) - \ln(P_{t-1})] \times 100 \quad (4.1)$$

where t refers to the period and P_t and P_{t-1} represent the closing price on day t and the previous day's stock closing price, respectively.[11]

4.5 Measurement of Volatility

This section describes the second indicator of volatility (variance), which illustrates the fluctuations of stock market returns. Volatility also measures the sensitivity of the stock market to changing circumstances, and it shows how the stock market reacted to the financial reforms announcement and events. In other words, returns indicate the future direction of stock market performance whereas variance is a measure of the risk in the market.

The traditional method that is used to measure the volatility of an asset return is calculated as the square of the standard deviation (variance) of a given continuously compounded return over a fixed period, such as price fluctuations of a service from one day to another or even from one month to the next or from one year to the next (Bhowmik & Wang 2020). A higher volatility is observed if a stock price fluctuates significantly. Conversely, a decreased volatility level is observed if the demand variation is small.

Stock market volatility has emerged as an important subject of interest in various pieces of finance literature, mainly because the worldwide financial markets have been highly interconnected and typically unpredictable. In addition, policymakers have used and

[11] There is an alternative method that is proposed by Parkinson (1980) to calculate the index returns that uses the (high/low) prices instead of (open/close) prices in Equation (4.1). Further, employing both (open/close) and (high/low) returns in one equation, as is suggested by Garman and Klass (1980), may draw a more comprehensive picture of the stock market. However, the daily closing prices of the Saudi stock indices are considered because of the unavailability and inaccessibility of the (high/low) prices from the Saudi stock indices data.

relied on financial volatility forecasts as measures of financial markets and the economy's vulnerability. For example, according to Nasar (1991), in a bid to establish the monetary policy of the agency, the United States Federal Reserve unreservedly considered the volatility of currencies, stocks, commodities and bonds. In GCC context, Hayat and Tahir (2021) found that the economic growth of Saudi Arabia UAE and Oman is positively determined by volatility of natural resources prices of these countries.

To obtain a better understanding of the statistical features of volatility, Liu et al. (2007) noted that volatility has significant practical benefits for traders because it allows for the quantification of risk, which is crucial for recognising instances in which stocks tend to be overpriced or underpriced. Wyplosz (2001) indicated that the probability of establishing a boom-bust cycle in a growing market is high because of capital mobility and financial liberation. According to Valentia et al. (2018), volatility is typically considered a monotonic proxy of stock market instability and risk.

This is largely a product of ineffective financial-policy frameworks that are aimed at combating extreme financial globalisation. For illustration, the global crisis and uncertainty have continued to be embedded in the operations of the world's financial system in emerging markets; however, volatility can be minimised through financial integration, which generates lending and borrowing opportunities for the international market, ensuring the diversification of portfolios (Das & Uppal 2004). In fact, Ackert and Smith (1993) argued that the volatility of stock prices stems from a change in the discount rate or from new details about future cash flows that are earned by shareholders. Similarly to Alqahtani et al. (2020), the returns volatility estimator σ_t^2 that is implemented is as follows:

$$\sigma_t^2 = [\ln(\frac{P_t}{P_{t-1}})]^2 \quad (4.2)$$

where σ_t^2 is the time-dependent variance, P_t refers to the closing price of the stock on day *t* and P_{t-1} refers to the closing price of the stock on the previous day $t\text{-}1$.

4.6 Descriptive Statistics

Descriptive statistics are commonly employed to determine the fundamental structure of data. They provide brief summaries of the data and their associated metrics. When descriptive statistics are presented with a graphical analysis, they serve as the foundation and starting point for the subsequent quantitative analysis. Descriptive statistics are used to validate the trend or pattern that is discovered via the use of diagrams in time-series data. This enables the identification of cyclical patterns, trends, major points and outliers. In the context of a time series, descriptive statistics focus primarily on the mean, the standard deviation, the skewness, the kurtosis and the Jarque–Bera test for normalcy (see Table 4.5).

Table 4.5: Summary of descriptive statistics methods used in this study

Method	Equation	Description
Mean	$\overline{x}_i = \frac{\Sigma x_i}{n_i}$	It is based on finding the central tendency of particular data. For this study, the mean is an essential tool in determining the average returns prices of the indices that are investigated.
Standard Deviation	SD = $\sqrt{\frac{\Sigma(x-\bar{x})^2}{n-1}}$	This statistical tool is essential for this study. It is useful for comparing the data discrepancies in the mean. The mean does not accommodate all the data because it only helps to find the central value of given data.
Skewness	$Sk = \sqrt{\frac{\sum_{i-1}^{n}(x-\bar{x})^3}{(n-1)\sigma^3}}$	This test indicates the presence or the absence of symmetry in particular data. A skewness value of 0 indicates an asymmetrical data set. Therefore, if skewness = 0, normal distribution skewness; if skewness > 0, positive skewness; and if skewness < 0, negative skewness.
Kurtosis	$K = \frac{n(n+1)(n-1)}{(n-2)(n-3)} \frac{\sum_{i=1}^{n}(x_i-\bar{x})^4}{(\sum_{i=1}^{n}(x_i-\bar{x})^2)^2}$	This method indicates the data's shape and the way that it differs from a normal distribution, including the slope or sharpness of the distribution of the data in a given set (Westfall 2014). In this case, there are three primary forms of distribution (if kurtosis > 3, leptokurtic distribution; if kurtosis < 3, platykurtic distribution; and if kurtosis = 3, normal distribution mesokurtic).
Maximum and Minimum	max = 1, 8, 6, $\overline{9}$, 3, 2 min= $\underline{1}$, 8, 6, 9, 3, 2	This method involves identifying the highest and the lowest data value (the maximum and minimum indices returns) for the study periods, which indicates the volatility of the indices returns at a given time. A high level of volatility is indicated by the difference between the maximum and the minimum level.
Jarque–Bera	$JB = \frac{n-k+1}{6}(Sk^2 + \frac{1}{4}(K-3)^2)$	This test is essential in terms of understanding the state of the information. The purpose of the Jarque–Bera test is to test the series normality distribution. The Chi-squared ($\chi 2$) statistic derives the null hypothesis, which is written as (H0: the data are normally distributed).

Note: Following the guidance of Brooks (2019), the descriptive statistics are obtained through the Econometrics-Views (EViews 10th edition) statistical software.

4.7 Saudi Stock Market (Risk-Adjusted) Performance

This section discusses one of the aims of this study, which was to examine the risk-adjusted performance of five relative Saudi stock indices (IS1, IS2, IS3, MS and CS). These selected stock indices are classified according to the IFPs across the full sample period and an additional subsamples investigation (before and after the financial reforms period). The Saudi stock market performance measurements contain SR, TR, JR and VaR and CVaR measurements.

4.7.1 Sharpe Ratio

This part of the thesis applies the SR to measure the stock market indices performance. Sharpe (1966) suggested a risk-adjusted performance approach that estimates the magnitude of excess returns per unit of an asset's total risk over the risk-free rate for a particular period. This method contains three components: the first is the daily returns of the index prices, the second is the risk-free rate and the third component is the global risk (standard deviation) of the daily returns. When comparing the indices' outcomes, a higher SR indicates a better index performance and vice versa. The following formula, in line with Ali et al. (2021), is used to calculate the SR:

$$SR = \frac{R_t - R_f}{\sigma_i} \tag{4.3}$$

where SR is the Sharpe ratio for the index, R_t is the average index returns, R_f is the risk-free rate for a specified period and σ_i is the standard deviation of the index returns for a specified period.

4.7.2 Treynor Ratio

This study also employs the Treynor (1965) ratio to evaluate the market indices performances. The TR as a method is similar to the SR in that the two methods indicate the performance of an equity. However, the TR incorporates systematic risk (β) into its equation instead of global risk, as in an SR estimation. As with SR, a greater TR indicates that the index outperforms the market and vice versa. According to Ali et al. (2021), the TR is estimated as follows:

$$TR = \frac{R_t - R_f}{\beta_t} \tag{4.4}$$

where TR is the Treynor ratio for the relative Saudi index, R_t is the average index returns, R_f is the risk-free rate for a specified period and β_t is beta of the Saudi stock index, which represents the systematic risk.

4.7.3 Value at Risk and Conditional Value at Risk

This study discusses value at risk (VaR), which is used to examine the risk-adjusted performance that relates to the returns of the five stock indices over the full study period (4 January 2010 to 29 June 2021) before and after the financial reforms program was introduced in Saudi Arabia in June 2015. The aim of employing VaR is to measure the maximum level of loss that the Saudi stock indices incur given a particular threshold of probability. In other words, an estimation of the daily VaR allows one to forecast the worst loss that is expected to occur for the relative index on the following day (Meloni et al. 2022; Simons 2000).

VaR incorporates various components of index price risk into a quantitative estimate of the probability of losing value over a specific period. For example, if the VaR for a specified index return has a 99% confidence level in period t_i, there is a 1% possibility that the index return is expected to decline by 2.33× σ_t during that time, t_i. Thus, VaR can be expressed as the following:

$$VaR_{\alpha} = Z_{\alpha}\sigma_t \tag{4.5}$$

where VaR_{α} is the expected loss for a selected relative index in a specified period, Z_{α} is the confidence interval rate and σ_t is the index returns standard deviation for a specified period.

Moreover, Rockafellar and Uryasev (2002) introduced a CVaR as a risk-adjusted performance indicator based on a weighted average over a specific timeframe. Whereas VaR assesses the maximum possible loss that may happen within a particular period with a certain degree of confidence, CVaR estimates the average loss over a period with a given level of confidence when the loss surpasses the VaR level. Thus, the CVaR equation is obtained in line with Adesi (2016) as follows:

$$CVaR_{\alpha} = \int_{-1}^{VaR} z dF_x^{\alpha}(z) \tag{4.6}$$

where

$$F_x^{\alpha}(z) = \begin{cases} 0, \text{when } z < VaR_{\alpha} \\ \dfrac{F_x(z) - \alpha}{1 - \alpha}, \text{when } z \geq VaR_{\alpha} \end{cases} \tag{4.7}$$

where F_x^α represents the probability density of obtaining a return with value (z), α is the VaR breakpoint and VaR is obtained from the established VaR level.

4.8 Stationarity and Unit Root Tests

This section discusses the employment of various unit root tests to the selected time series because this study aimed to capture the volatility spillover in the oil market (Brent and WTI) or the US stock market (S&P 500) and five Saudi stock indices that are classified by IFPs. According to Bollerslev (1986), modelling volatility (conditional variance) by using GARCH-type models requires data to be stationary. More specifically, a stationarity condition in the time-series data indicates almost-constant mean, variance and autocorrelation. Therefore, time-series econometric methods allow the data set to be stationary in the estimation of the parameters (Gujarati & Porter 2009; Maddala 2001; Maddala & Wu 1999; Shrestha & Bhatta 2018). However, if inferential statistics, such as t-statistics and F-measures, are correctly interpreted by means of a regression analysis then misleading results are obtained (Philips & Perron 1988). Therefore, the basic approach that is used to test the serial stationary is the unit root test (Dickey & Fuller 1979; Dickey, Bell & Miller 1986).

ADF, PP and KPSS are widely conducted unit root tests in financial time-series studies (Rothe & Sibbertsen 2006; Shrestha & Bhatta 2018). Further, employing these various techniques helps in that the verdict of one method confirms the other techniques. Therefore, multiple tests that use the ADF, PP and KPSS methods are used in this study for a unit root in a level and first-series tests are used to ensure confidence in the outcomes of the analyses.[12]

[12] Either the ADF or the PP method can be carried out with the addition of a constant and a linear pattern or only a constant term (Al-Khazali et al. 2006; Boschi 2007; Egert & Kocenda 2007).

4.8.1 Augmented Dickey–Fuller Test

This section describes the implementation of Dickey and Fuller's (1979) ADF test, which is initially performed to check the trend-stationarity time-series data. The ADF test examines whether there is a unit root in a time-series data set (Horváth, Kokoszka & Rice 2014). Meanwhile, the data may be considered stationary if the trend does not change over time. In such a case, it is concluded that a unit root exists. The basis of rejecting a null hypothesis that arises from the tests is the *t*-statistic, which is always a negative number (Jentsch & Rao 2015). A significant and negative *t*-statistic value implies a rejection of the null hypothesis where there is a unit root at the 95% confidence level. Thus, the estimable ADF test equation is specified as:

$$\Delta Y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \delta_2 \Delta y_{t-2} + \cdots + \delta_p \Delta y_{t-p} + \varepsilon_t \tag{4.8}$$

where ΔY_t represents the difference of a time series of the study-selected (local and global) indices in which $\Delta Y_t = y_t - y_{t-1}$, α is the constant that is represented by the intercept, β represents the coefficient of a time trend (t) and ε_t refers to the residual (error) term. While testing the null hypothesis (H_0: $\gamma = 0$, there is a unit root within the time series) or an alternative hypothesis (H_1: $\gamma < 0$, no unit root test within the time series), the *t*-statistic is compared to the relevant critical value (Paparoditis & Politis 2018). As a result, the null hypothesis (H_0: $\gamma = 0$) is rejected if the *t*-statistic reports less than a critical value and concludes that the unit root is not present (Dickey 2015).

4.8.2 Phillips–Perron Test

This section describes the second stationarity test, the PP test, for this study, which was developed by Phillips and Perron (1988) to analyse the presence of a unit root in a time series. Unlike the ADF test in the previous section, the PP test is a non-parametrical statistical method that does not require the selection of the level of serial correlation. More specifically, the PP test has a less restrictive nature of the error process because it corrects any serial correlation or heteroscedasticity in the errors of the time-series data (Spyridisa, Sevicb & Theriouc 2010). Thus, the PP test is based on the following equation:

$$\Delta Y_t = \alpha + \rho y_{(t-1)} + \varepsilon_t \tag{4.9}$$

where $\Delta \mathrm{Y}_t$ refers to the difference of a time series of the study-selected (local and global) indices in which $\Delta \mathrm{Y}_t = \mathrm{y}_t - \mathrm{y}_{t-1}$, α is the constant and ρ is the coefficient of the non-parametric correction in the PP equation to optimise for some characterisations such as any serial correlation and heteroscedasticity in the white noise error term (ε_t). Similar to the ADF test, the null hypothesis (H_0: $\gamma = 0$) assumes the existence of a unit root in a time series (non-stationarity). If the *t*-statistic rejects the H_0, the alternative hypothesis is accepted (H_1: no unit root in a time series), which indicates that the data are stationary.

4.8.3 Kwiatkowski, Phillips, Schmidt and Shin Test

This section presents an additional method to examine the existence of a unit root (data stationarity) in the selected Saudi and global index series. Kwiatkowski et al. (1992) developed this technique to outperform the ADF tests' issue of a lack of power when significant evidence of stationarity is near unit root processes. According to Spyridisa et al. (2010), the KPSS test indicates that the time series consists of a deterministic trend, a random walk and a stationary error. Accordingly, the time series is presented as follows:

$$Y_t = \alpha + \delta_t + x_t + \varepsilon_t \tag{4.10}$$

where Y_t refers to the sum of the deterministic trend of a time series of the study-selected (local and global) indices, α is the constant, δ_t represents the deterministic trend and x_t refers to the random walk in which $x_t = x_{t-1} + v_t$; here, $v_t \sim (0, \sigma_v^2)$ and ε_t is the stationary error that has a mean value equal to 0. Then, the one-sided Lagrange Multiplier (LM) test is considered to examine the null hypothesis that states that ($H_0 \colon \sigma_v^2 = 0$), which indicates the trend stationarity of the time series Y_t. However, the alternative hypothesis (H_1) states that the time series contains a unit root.

Once the stationarity of the data is confirmed, this study can pursue other diagnostical tests (e.g. multicollinearity test, Granger causality test, and ARCH effect test) before applying the GARCH framework for the volatility persistence analysis and the volatility spillover investigation.

4.9 Test for Multicollinearity

This section describes the Pearson's multicollinearity matrix used to determine whether the selected global markets (Brent, WTI and S&P 500) correlate with others. The correlation, according to Levine et al. (2008), reflects the relative strength of the linear link between the variables (markets). Therefore, discovering the correlation between the indices helps to confirm and to improve the employment of the indices in the selected model. More specifically, correlations between markets returns of 0.8 or higher may encounter a problem of multicollinearity in volatility spillover estimation (Natarajan, Singh & Priya 2014). According to Karmakar and Shukla (2016), multicollinearity issues in the stock market returns may cause poor predictions or insignificant estimations of the volatility spillover that is obtained from the GARCH framework.

4.10 Test for Granger Causality

This section discusses the Granger causality test, which was established by Granger (1969) and then developed by Granger (1981), Engle and Granger (1987) and Granger and Hallman (1991). The Granger causality test is conducted in this study to examine whether there is any causal relationship between the selected markets before conducting the volatility spillover investigation. In other words, the test aims to statistically justify whether the daily returns of the selected global indices (Brent, WTI and S&P 500) are useful for estimating the returns of the Saudi stock indices (IS1, IS2, IS3, MS and CS). The null hypothesis of this test consists of no Granger causality between the two indices and is written as follows:

H_0: The global index (Brent, WTI or S&P 500) does not Granger cause the Saudi stock index (IS1, IS2, IS3, MS and CS).

Meanwhile, the alternative hypothesis, which states that the two indices affect each other, is written as follows:

H_1: The global index (Brent, WTI or S&P 500) Granger causes the Saudi stock index (IS1, IS2, IS3, MS and CS).

If the *F*-test is less than the significant level, the null hypothesis is rejected. As a result, it can be concluded that the global index Granger causes the Saudi index and vice versa. According to Hasbullaha, Rusyaman and Kartiwa (2020), if the Granger causality test proves the causal relationship between the markets, the next stage of analysis can proceed.[13]

[13] For more information about the Granger causality test, see Brooks (2019).

4.11 Statistical Models

The purpose of this chapter is to describe the analysis methods of using various types of GARCH models to measure volatility spillover. This allows for an effective examination of the interrelationship between the global markets (Brent crude oil, WTI or S&P 500) and five stocks indices that are categorised to address IFPs. This allows for continuous improvement in risk management and better decision-making about portfolio diversification.

4.12 Test for ARCH Effect

This section describes the Lagrangian Multiplier (LM) diagnostic test, which was presented by Engle (1982). The ARCH-LM test examines the presence of the ARCH effect in the squared residuals of the estimated model. The use of the ARCH-LM test validates the pursuit of the GARCH framework. Furthermore, neglecting the ARCH-LM test may lead to inefficiencies when running the GARCH models (Gujarati & Porter 2009). Checking the heteroscedasticity of a regression's residuals is a reasonably straightforward process.

This form of ARCH effect test is based on ordinary least squares (OLS) regression, in which residuals of OLS are maintained. Moreover, the OLS model is homoscedastic is considered as the null hypothesis (H_0), which indicates the lack of ARCH effect, and is presented as the following:

$$y_t = \alpha x_t + \varepsilon_t \tag{4.11}$$

in which ε_t is the white noise. If the H_0 is rejected, it is concluded that ε_t has the ARCH effect. The purpose of the test is that if the ARCH effect is diagnosed, the current value of ε_t can be predicted from the previous value of ε_t. In other words, the ARCH-LM test detects the ARCH effect within the study data sets by using Chi-squared (χ^2) statistics, which indicate the existence of volatility clustering in the residuals. Therefore, this study is able to pursue the extended GARCH framework, which is conducted for the volatility persistence analysis and the volatility spillover investigation (Goudarzi & Ramanarayanan 2010).

4.13 Univariate GARCH Models

This section describes the estimation of multiple univariate GARCH models, which aims to ensure that the conditional variance processes properly suit the returns series. Intensive empirical investigations demonstrate that the GARCH representations are effective in capturing the volatility and its features in the context of stock markets (Bollerslev et al. 1988; Chun et al. 2019; Engle & Ng 1993; Engle & Siriwardane 2018; Janani Sri et al. 2022; Mallikarjunappa et al. 2008; Pati & Rajib 2011). Symmetric GARCH (1,1), asymmetric EGARCH (1,1) and GJR-GARCH (1,1) models are conducted to investigate the volatility and its persistence in Saudi stock index returns, which provide more robust explanations for conditional volatility (Wang & Yang 2018).

In this context, volatility persistence refers to the extent to which past fluctuations influence current volatility and remain significant over a longer time frame (Coffie 2015). Therefore, measuring the returns of the Saudi stock indices is a crucial determinant of volatility persistence (Bollerslev et al. 1988; Coffie 2015; Naimy et al. 2021). Further, considering the Saudi financial reforms period would explain a new behaviour for the volatility and its characteristics. More specifically, comparing the volatility and its persistence before and after the reforms can provide empirical evidence to help to improve the estimations of volatility and its implications in the future.

Moreover, before investigating the volatility spillover through the ARMA-GARCH, the cross-correlation function (CCF) test and the bivariate GARCH approaches, it is essential to define the univariate GARCH model. The ARMA-GARCH, CCF and Baba–Engle–Kraft–Kroner (BEKK) representations use the benchmark univariate GARCH (1,1) as a base step in their procedures.[14]

4.13.1 Univariate GARCH (1,1)

This section explains the employment of the symmetrical univariate GARCH (1,1), which is the general equation that specifies the GARCH models and in this analysis the conditional variance is denoted as its own lag linear function (Brooks 2019). The equation is as follows:

$$r_t = \mu + \alpha r_{t-1} + \varepsilon_t, \varepsilon_t \sim N\ (0, \sigma_t^2) \tag{4.12}$$

Equation (4.12) represents the mean equation of the univariate GARCH model where r_t is the return at the present time for the selected eight data series i in which [i = 1, IS1; i = 2, IS2; I = 3, IS3; I = 4, MS; I = 5, CS; I = 6, Brent; I = 7, WTI; and I = 8, S&P 500], μ is the constant term that includes autoregressive (AR) and moving average components (MA), α is the coefficient for past returns and ε_t is the residual (error term) in the mean equation. Thus, GARCH (1,1) is given as follows:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{(t-1)}^2 + \beta\sigma_{(t-1)}^2 \tag{4.13}$$

[14] The standard GARCH model was introduced by Engle (1982) and Bollerslev (1986). GARCH models are powerful tools in the analyses of financial time-series data. They capture the fluctuation in a data set and estimate the direction of the stock market at the same time. The GARCH framework is far superior to any other homoscedastic model statistical tool (e.g. OLS) in terms of statistical power and the conceptual framework (Engle, Focardi & Fabozzi 2012).

In Equation (4.13), N denotes the mean of the conditional normal density, σ_t^2 refers to the conditional variance and ω is the constant of the variance equation. Furthermore, the lag order of the ARCH and GARCH processes is represented by (1,1) whereas the corresponding α and β are the coefficients for the ARCH and GARCH specifications, respectively. The model is subjected to non-negativity constraints, $\omega > 0, \alpha_1 \geq 0$ for $i = 1$ and $\beta_1 \geq 0$ for $j = 1$, to ensure that σ_t^2 is positive.

4.13.2 Univariate Exponential GARCH (1,1)

This section discusses the model of Nelson (1991), who developed an alternative GARCH model using the specifications of the logarithmic volatility called EGARCH. Unlike the symmetrical GARCH (1,1) model, the GARCH and EGARCH are capable of dealing with clustering and leptokurtosis when modelling volatility; however, GARCH (1,1) is not able to capture the asymmetrical (leverage) effects between index returns and volatility changes, which is a crucial element when handling financial time-series data. Advantageously, the EGARCH model can capture an asymmetrical impact, which, according to Black (1976), characterises the tendency for negative news to magnify conditional volatility more than positive news of a similar size. Rather than simply displaying the conditional difference, EGARCH simulates the normal logarithm of the fluctuation (volatility), so no bounding constraints are required to ensure a positive bounding change (Hung 2018; Jebran et al. 2017; Poon & Granger 2003). Thus, the EGARCH (1,1) equation, according to Brooks (2019), can be written as follows:

$$r_t = \mu + \alpha r_{t-1} + \varepsilon_t, \varepsilon_t \sim N\,(0, \sigma_t^2) \tag{4.14}$$

$$Ln(\sigma_t^2) = \omega + \beta Ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \tag{4.15}$$

where σ_t^2 represents the conditional variance, ω is the constant and β refers to the coefficient of the previous conditional variance ($\beta > 0$ and $\beta < 1$ to maintain stationarity). Further, γ is the coefficient that represents the asymmetrical (leverage) effect in the model, which implies that the conditional volatility would be affected differently by good and bad news. More specifically, asymmetrical status exists when $\gamma > 0$ and leverage effect exists when $\gamma < 0$ (Iqbal et al. 2021; McAleer & Hafner 2014). Meanwhile, in case $\gamma = 0$, then the impact of news is symmetrical (Dyhrberg 2016; McAleer 2014; Ural & Demireli 2020). Moreover, α is the coefficient that measures the size effect of a standardised past shock (Ngene et al. 2014), which is required to be negative to ensure asymmetry (Tsay 2013). If the sign of α is positive, this indicates that the positive news influences the volatility more than the negative news.

4.13.3 Univariate GJR-GARCH (1,1)

This section highlights Glosten, Jagannathan and Runkle's (1993) GJR-GARCH model, which was developed to identify the asymmetric impact on the financial time series. Many studies choose to employ GJR over other members of the GARCH family because of the performance superiority of this model when applied directly to stock market returns (Engle & Ng 1993; Engle & Siriwardane 2018). Furthermore, the GJR-GARCH model has less complexity than the EGARCH because the modelling of volatility (conditional variance) is directly implemented instead of employing the natural logarithm (Hayashi 2000). To assess the negative and positive information about conditional variance, this study incorporates GJR-GARCH (1,1), which includes an additional dummy variable that has a residual square. Thus, Brooks (2019) illustrates that the GJR-GARCH (1,1) model can be stated as follows:

$$r_t = \mu + \alpha r_{t-1} + \varepsilon_t, \varepsilon_t \sim N\ (0, \sigma_t^2) \tag{4.16}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1} \tag{4.17}$$

In this equation, ω is the constant term of the GJR-GARCH equation and γ is the coefficient of the asymmetrical effect. To elaborate, if γ is statistically significant, the conditional volatility is affected differently by positive and negative news (Epaphra 2017). Good news has an effect only on α whereas bad news affects α and γ. If γ is significant and positive ($\gamma > 0$), then the news effect is asymmetrical. However, if ($\gamma = 0$), the effect of the news is symmetric. Furthermore, I_{t-1} is a dummy variable in which (I_{t-1}=1, if $\varepsilon_{t-1} < 0$, positive news; and I_{t-1}= 0, if $\varepsilon_{t-1} \geq 0$, negative news).[15]

4.13.4 Volatility Persistence

This section extends the estimate of the conditional volatility by simultaneously measuring the persistence of conditional variance (volatility). As was mentioned earlier, volatility persistence can be defined as the degree of fluctuations that make the current volatility vital in the future (Coffie 2015). The persistence of volatility affects an asset's price (Fama & French 1988; Poterba & Summers 1986). Specifically, an increase in (anticipated) volatility persistence leads to a decline in the price of the Saudi stock index. Thus, it can also assist in quantifying the risk premium of the Saudi stock index.

[15] GJR-GARCH functions identically to Zakoyan's (1994) TGARCH. In the two models, the residual square filters information.

Accordingly, identifying the persistence of volatility can therefore improve the understanding of future volatility, which is vital for portfolio managers and policymakers.

Moreover, a positive or negative return helps to forecast the stock index volatility for a specific period in the future and vice versa (Emenogu et al. 2020; Epaphra 2017; Green & Figlewski 1999) wherein greater and longer durations of volatility result in a positive correlation between volatility and returns. Higher levels of volatility correlate with a higher likelihood of gaining larger returns (Ang & Liu 2007). However, the leverage or asymmetric effect may assist in forecasting volatility when encountering negative returns that increase volatility; however, positive returns do not instantly decrease volatility (Bandi & Renó 2012). Therefore, this study measures the volatility persistence by using the symmetric and asymmetrical GARCH models that were described in previous sections.[16]

For the symmetric GARCH (1,1) model in Equation (4.13), the volatility persistence measurement is determined by the sum of the coefficients ($\alpha + \beta$; Bollerslev 1986; Kambouroudis 2016; Malik et al. 2005; Naimy et al. 2021). More specifically, the closer the value of $(\alpha + \beta)$ is to 1, this indicates a higher volatility persistence in the index returns series (Naimy et al. 2021; Olowe 2009). Therefore, this implies that when volatility persistence is large in magnitude, it takes a long time for the index returns volatility to subside (die out). According to Epaphra (2017), when the sum of $\alpha + \beta$ is equal to 1, a current shock persists for an extended period. In other words, a high value for $\alpha + \beta$ indicates a 'long memory' and any shock may cause a permanent change to

[16] According to Andersen and Bollerslev (1998), GARCH framework can accurately estimate volatility once volatility persistence is accurately calculated.

volatility in the future, which suggests that conditional volatility is persistent (Chaudhary, Bakhshi & Gupta 2020).

Given that the GARCH (1,1) is limited to symmetric natural, to include the asymmetrical effect and persistence when considering volatility estimations, the study uses EGARCH (1,1) and GJR-GARCH (1,1). For the asymmetric EGARCH (1,1) model in Equation (4.15), the asymmetric effect is identified by the coefficient γ and the volatility persistence is captured by β in which a larger value of β indicates a higher level of volatility persistence and when it is closer to 1 it indicates that volatility persists (Alexander 2009; Chu et al. 2017; Naimy et al. 2021). Further, these studies indicate that volatility persistence helps investors and portfolio managers who encounter asymmetric and leverage effect when forecasting volatility. Moreover, for the GJR-GARCH (1,1) model in Equation (4.17), $(\alpha + \beta + \frac{\gamma}{2})$ represents the persistence in the volatility of the Saudi stock index returns (Chu et al. 2017; Naimy et al. 2021; Nugroho et al. 2019).

4.13.4.1 Half-lives perspective

To determine the volatility shocks in the Saudi stock indices, this section considers the employment of the half-lives perspective for volatility persistence, which helps to quantify the number of days over which a volatility shock of the Saudi stock indices diminishes to half of its initial magnitude. Obtaining the volatility persistence through the half-life method is employed to measure the impact of changing volatility in the stock market (Chou 1988). Therefore, policymakers gain insight into market expectations and policy uncertainty. According to Erdemlioglu et al. (2012) and Epaphra (2017), understanding and estimating market volatility is significant for pricing assets, for allocating portfolios and for managing risks. Therefore, this study aimed to capture the change in volatility persistence behaviour by employing comparative analyses between the two periods (pre and post reform).

According to Engle and Patton (2001), the volatility half-life is the time that is required for the volatility to move halfway back towards its unconditional mean. Half-life is commonly used to illustrate the difference in shock persistence. A half-life measures the period (in days) that is required for a volatility shock to reduce to half its initial magnitude (McMillan & Thupayagale 2011). Thus, the half-lives of volatility persistence, according to John et al. (2019), can be calculated as follows:

$$HL_{GARCH} = \frac{Ln(0.5)}{Ln(\alpha + \beta)} \tag{4.18}$$

$$HL_{EGARCH} = \frac{Ln(0.5)}{Ln(\beta)} \tag{4.19}$$

$$HL_{GJR-GARCH} = \frac{Ln(0.5)}{Ln(\alpha + \beta + \frac{\gamma}{2})} \tag{4.20}$$

where *HL* represents the half-life concept. In Equation (4.18), α and β refer to the volatility persistence coefficients relative to GARCH (1,1). β in Equation (4.19) measures the volatility persistence for the EGARCH (1,1) model. Finally, $\alpha + \beta + \frac{\gamma}{2}$ in Equation (4.20) measures the persistence of volatility for the GJR-GARCH (1,1) model.[17]

[17] For more information about the HL method for GARCH models, see Olowe (2009).

4.14 Investigation of Volatility Spillover

This section of the study identifies the aim of investigating the existence of volatility spillover between the Saudi stock market and three global indices by implementing three well-established volatility spillover techniques. First, the study employs the ARMA-GARCH (1,1) approach for the global market (oil market and US stock market) in the mean equation to capture the returns volatility transmissions (spillover) to the selected Saudi local indices. Second, the study examines the volatility spillover by using the CCF method that was developed by Cheung and Ng (1996), which uses the estimation of the univariate GARCH model, which allows for the testing of the causality in variance between two time series. The third approach uses a multivariate GARCH (MGARCH) model prediction, which analyses the causality relationship among variables by limiting certain parameters. Although MGARCH models have been commonly used in other studies, MGARCH models' power benefits outweigh the broad-scale data set (Hafner & Herwartz 2006).

4.14.1 Volatility Spillover: ARMA-GARCH (1,1) Approach

This section describes the implementation of the ARMA and GARCH (1,1) techniques for investigating the volatility spillover from global indices returns (Brent, WTI and S&P 500) to the Saudi stock market returns (IS1, IS2, IS3, MS and CS). The ARMA model is performed to model its error by using GARCH (1,1) between the Saudi stock index returns and one of the global indices returns (Chen & Huang 2010).[18] According to Dedi and Yavas (2016), this method employs a similar process to that of the univariate CARCH (1,1) model by Bollerslev (1986) however it differs in the inclusion of an exogenous

[18] According to Kumar and Mukhopadhyay (2007), the ARMA-GARCH model's performance is superior to that of other complex MGARCH models.

factor (global index) in the mean equation to estimate the current volatility of the Saudi stocks indices returns series. The model is expressed as follows:

$$r_t = \mu + \alpha x_{t-1} + \varepsilon_t,\ \varepsilon_t \sim N(0, \sigma_t^2) \tag{4.21}$$

where r_t is the daily return of the selected Saudi indices at period t, x_t is the daily return of the global index (Brent, WTI or S&P 500) and ε_t is the residual (error) term in the mean equation. Then, the GARCH (1,1) model is fitted when the errors of regression (mean) model has a standardised residual sequence ~ that has mean = 0 and variance = 1 and N donates the distribution of the stock index returns. Thus, the conditional variance is conducted by using the GARCH (1,1) model, which is specified as follows:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{(t-1)}^2 + \beta_1 \sigma_{(t-1)}^2 \tag{4.22}$$

where σ_t^2 represents the conditional variance at the current time, ω is the constant, α_1 is the error term conditional on the lag information (ARCH) and β_1 is the coefficient of the lag value of the conditional variance (GARCH). In the case of measuring volatility spillover, the GARCH term denotes the exogenous factor (global indices) that have an influence on the Saudi index returns volatility σ_t^2.

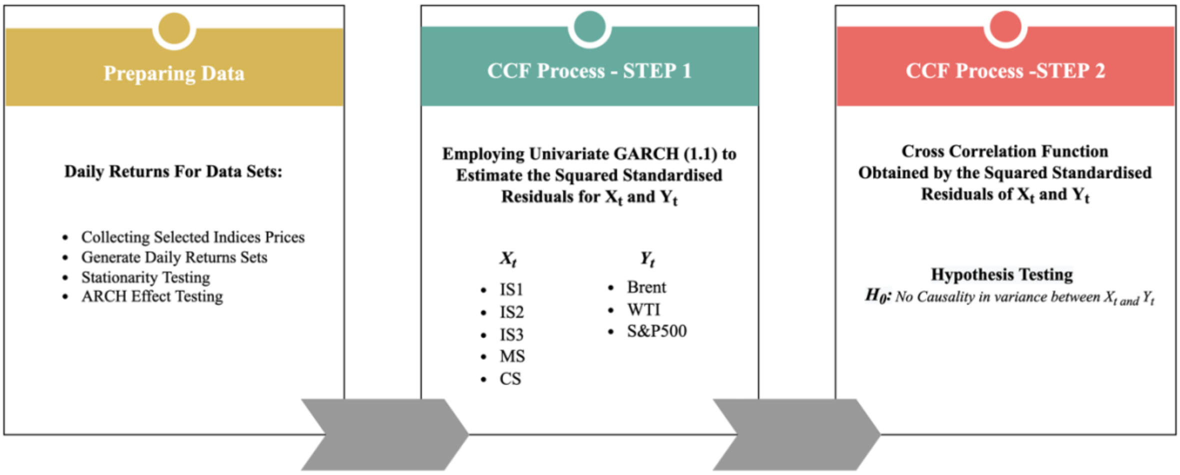
The objective of including these global indices (Brent, WTI and S&P 500) was to employ them as an exogenous indicator in the mean Equation (4.21) for the returns of the Saudi stock indices. Prior to conducting the model, it is necessary to ensure that the index time series passes the stationarity tests. Then, it is justified by the Granger causality test. Meanwhile, the number of global indices to include in the model can be determined according to the correlation analysis between these indices (Yeasin et al. 2020). The next step is to determine whether the returns volatility of the Saudi stock indices is affected (spillover) by the lag volatility of the global market returns. The impact is evaluated by examining the *t* statistical significance of the GARCH coefficient of individual global indices.

4.14.2 Volatility Spillover: Cross-Correlation Function Approach

This section describes Cheung and Ng's (1996) causality in variance test that uses the CCF, which is implemented to investigate volatility spillover. According to Toyoshima (2018), the causality in variance CCF technique has been extensively implemented in studies of financial markets such as stock, fixed income, commodities and derivatives markets. The rationale of performing this test is to establish the ways that the information flows from one financial market to another. In this study, the volatility of oil prices (Brent and WTI) and the global stock market (S&P500) influences the volatility of the Saudi stock market, including five Saudi indices that are categorised under three classes according to IFPs.

It is expected that the test confirms that the volatility of the Saudi stock market is caused by the volatility in oil prices and the global index. If the CCF test establishes causality, which is likely, it is an additional justification for the inclusion of oil price volatility and global index volatility as external factors in the more comprehensive MGARCH, which is discussed in the next section. According to Cheung and Ng (1996) and Hong (2001), the CCF technique can give meaningful information when constructing multivariate MGARCH models. As a result, the CCF has increased efficiency when modelling volatility.

Figure 4.2: Elaboration of study's implementation of the causality in variance test according to CCF processes.



Notes: Refer to list of abbreviations for more clarifications.[19]

The causality in variance (CCF) test, according to Cheung and Ng (1996), follows two steps (see Figure 4.2). The first is to employ two individual univariate GARCH models, as was previously specified in Equation (4.13), to obtain the standardised squared residuals for the two indices: one index for the oil market (Brent or WTI) or global stock market index (S&P 500) and the second index for one of the five stock indices (IS1, IS2, IS3, MS and CS) that are categorised into three classes of assets to address IFPs in the Saudi stock market.

The second step in the CCF test process is to establish a test statistic by using the standardised squared residuals function to deduct the causal relationship between the selected indexes. Chi-squared (χ^2) statistics are conducted to examine the null hypotheses of no causality in variance between the two series of data, which is established in the first

[19] This diagram is drawn by the researcher.

step.[20] The null hypothesis that uses χ^2 statistics (there is no causality in variance) is written as follows:

H_0: There is no causality in variance (spillover) from the (oil market/global stocks index) volatility to the returns volatility of the five assets indices that use IFPs in the Saudi stock market.

When the null hypothesis cannot be rejected, this indicates that the standardised squared residuals for the two indices do not have a cross-correlation relationship.

4.14.3 Volatility Spillover: Multivariate GARCH Approach

This section aims to extend the investigation of volatility spillover by employing a multiple indicators model. MGARCH models are capable of outperforming the univariate GARCH method and Cheung and Ng's (1996) CCF test in terms of capturing volatility spillover.[21] Meanwhile, the CCF test only analyses conditional variance, MGARCH models' volatility and its spillover by using conditional variance and covariance (Caporale et al. 2002).

Further, the volatility spillover between the oil market (Brent and WTI) or the US stock market (S&P 500 Index) and the five Saudi stock indices (IS1, IS2, IS3R, MS and CS) is examined by using a multivariate GARCH-type model, which covers the three categories of stocks that use IFPs.

Therefore, this study adapts the BEKK type of the MGARCH models, which were introduced by Engle and Kroner (1995). According to Caporale, Pittis and Spagnolo

[20] For the specifications of the mathematical definition of the CCF test, see Cheung and Ng (1996).
[21] Kondoz et al. (2019) suggested that MGARCH techniques are more prevalent than univariate approaches, particularly when investigating the volatility spillover between a variety of time series. This method generates a conditional variance matrix structure, which is essentially a simultaneous equation for time series, unlike the two-step test that is used in the univariate GARCH method.

(2002), the M-GARCH-BEKK type is widely used to investigate spillover between financial time series. One reason that the BEKK approach is commonly used is the capability of its process to include potentially influential factors. In other words, the model captures the causes of conditional volatility and quantifies volatility transmission across time series simultaneously.

The study reviews several MGARCH approaches and decides to employ the most frequently used multivariate GARCH-BEKK approach in this investigation (Zolfaghari et al. 2020). The BEKK approach overcomes serious concerns that are associated with other MGARCH types, such as Bollerslev, Engle and Wooldridge's (1988) VECH model and Bollerslev's (1990) constant conditional correlation (CCC) model. Although the VECH model is found to be a complex approach because of the high number of coefficients that must be considered, which results in the use of a relatively low degree of freedom in the estimation process,[22] the CCC model simplifies the complexity of the VECH model estimation by adjusting the restrictions on the variance-covariance matrix that is produced from the system of simultaneous equations. However, the CCC form of MGARCH has limitations, including the assumption of constant correlations in the system of equations among its components. It is seen to be unreasonable because the model does not ensure positive definiteness when estimating variance-covariance matrices. Therefore, the CCC model is incapable of solving the system of equations because the estimate of the model coefficients fails when the variance-covariance matrix is negative.

To avoid the VECH and CCC concerns, a multivariate GARCH-BEKK model is used in this investigation. The BEKK method is used to parameterise the original system of

[22] According to Wang, Pan & Wu (2018), it is more likely that complex estimation with greater estimation error would lead to a worse prediction outcome.

equations by using a quadratic form to assure the positive definiteness of the variance-covariance matrix without significantly affecting the information content of the system of the equation (Brooks et al. 2003; Tsay 2005; Zolfaghari et al. 2020).

Although the BEKK model has fewer parameters than the VECH model, it is still impractical to include all the study-selected indices in one equation, which would result in a huge number of parameters. Moreover, in the case of extending the BEKK model to include more variables (indices), the estimation process of the model becomes more complex and even impossible in some cases (Ashfaq et al. 2019; Bauwens et al. 2006; Ledoit & Wolf 2003; McAleer et al. 2009). Therefore, a bivariate GARCH-BEKK technique is employed in this investigation.

In this framework, the conditional variance of the Saudi market is influenced not only by its own prior shocks and conditional volatility but also by the prior shocks and conditional volatility of the global market (Brent, WTI or S&P 500). Therefore, BEKK, CCC and dynamic conditional correlation (DCC) bivariate GARCH techniques allow the measuring of the spillover existence and its magnitude of information shocks and volatility between markets and the identification of the direction of the spillover. Moreover, it allows the employment of the estimate outcomes to compute the optimal weights for portfolio management and hedge ratios.

4.14.3.1 Bivariate Baba, Engle, Kraft and Kroner approach

This section further explains the process and the specifications of the study-adapted bivariate GARCH-BEKK model in the context of a Saudi Arabia stock market volatility spillover investigation. The bivariate GARCH-BEKK model is capable of establishing a variance and covariance H_t matrix because the BEKK estimation is flexible and can count its own and cross-market volatility spillover relationships. In this study context, the variance-covariance matrix H_t depends on the past shocks and the symmetrical volatility of the stocks index in the Saudi stock market and one of the global markets' (Brent, WTI or S&P 500) shocks and volatility. First, the conditional mean (returns) equation is modelled through a vector autoregressive (VAR) model, which is described as follows:[23]

$$R_t = \mu + \alpha R_{t-1} + \varepsilon_t, \tag{4.23}$$

$$\varepsilon_t \sim N(0, H_t) \tag{4.24}$$

where $R_t = (r_t^L, r_t^G)$ is the returns matrix of the Saudi stock index (L = IS1, IS2, IS3, MS or CS) and one other global market (G = Brent, WTI or S&P 500) at time *t*, respectively, μ is a 2×1 vector of constant terms, α is a (2×2) coefficients matrix for past returns and $\varepsilon_t = (\varepsilon_t^L, \varepsilon_t^G)$ is a 2×1 vector of the residuals (error terms) from the mean equations for the two markets, L and G (local and global), respectively. Meanwhile, ε_t, as is specified in Equation (4.24), is the residual of the mean equation, which is derived and follows a normal distribution in which the mean is 0. Moreover, the conditional variance and covariance matrix H_t of the residuals are established.

Thus, as an extension of the univariate GARCH in Equation (4.13), in the bivariate model, one must consider *n*-dimensional stochastic processes, which includes a conditional covariance matrix (H_t) and zero-mean random variables (X_t). The BEKK type of the bivariate GARCH models, which was introduced by Engle and Kroner (1995), imposes positive definiteness restrictions and guarantees the positivity of the conditional variance and covariance matrices (H_t). Thus, H_t is presented as in the following covariance matrix:

[23] According to Jayasinghe, Tsui & Zhang (2014) and Mensi et al. (2014), implementing VAR into a conditional mean equation (Equation (4.23) improves the accuracy of estimations.

$$H_t = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} \tag{4.25}$$

Here, h_{11} represents its own past effect on the Saudi market (L), h_{12} is the effect of the L market (Saudi market) on the G market (global market), h_{21} is the effect of the G market on the L market and h_{22} indicates the past effect of the global market. The following BEKK (*p, q*) model is how it is generally specified:

$$H_t = CC' + \sum_{i=1}^{q} A_i' \varepsilon_{t-i} \varepsilon_{t-i}' A_i + \sum_{j=1}^{p} B_j' H_{t-j} B_j \tag{4.26}$$

Next, the components for the matrices *C, A* and *B* are given as:

$$C = \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix}, A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}, B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \tag{4.27}$$

In Equation (4.26), H_t refers to the conditional variance-covariance matrix for a Saudi stock index (IS1, IS2, IS3, MS or CS), which is categorised into one of three groups according to IFPs. *C* and *C'* are the lower triangular matrices of the constants and ensure the positive definiteness of H_t through its parametrisations. A_i and B_j represent the parameters that estimate the matrices of one selected Saudi stock index and one global index (Brent, WTI or S&P 500) where $\varepsilon_{t-1}\varepsilon_{t-1}'$ refers to the lagged value of shock in the mean equation. Further, *t* refers to the time and represents the current daily returns volatility for time *t* and *t-i* represents the returns volatility in the previous period (time *t-i*).

The number of parameters in the bivariate GARCH-BEKK (1,1) model is calculated as follows:[24]

$$P = \frac{N(5N+1)}{2} \tag{4.28}$$

where P refers to the number of parameters in the bivariate GARCH-BEKK estimation process and N is the number of included indices (markets) in the model. The number of relevant time series in the case of the bivariate GARCH-BEKK is two (N = 2). Therefore, 11 parameters are estimated for each bivariate GARCH-BEKK (1,1) equation.

Then, the bivariate GARCH-BEKK (1,1) representation is expanded as follows:

$$\begin{aligned} H_t = {} & \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix} \begin{bmatrix} c'_{11} & c'_{12} \\ c'_{21} & c'_{22} \end{bmatrix} \\ & + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1}\varepsilon'_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon'_{1,t-1} & \varepsilon^2_{2,t-1} \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \\ & + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \end{aligned} \tag{4.29}$$

The BEKK matrix can be expanded and can derive equations for the conditional variance and the conditional covariance as follows:

$$\begin{aligned} h_{11,t} = {} & c^2_{11} + c^2_{21} + a^2_{11}\varepsilon^2_{1,t-1} + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a^2_{21}\varepsilon^2_{2,t-1} \\ & + b^2_{11}h_{11,t-1} + 2b_{11}b_{21}h_{12,t-1} + b^2_{21}h_{22,t-1} \end{aligned} \tag{4.30}$$

[24] For more explanations, see Engle and Kroner's (1995) study.

$$h_{12,t} = c_{12}c_{22} + a_{11}a_{12}\varepsilon_{1,t-1}^2 + (a_{21}a_{12} + a_{11}a_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}a_{22}\varepsilon_{2,t-1}^2 + b_{11}b_{12}h_{11,t-1} + (b_{21}b_{12} + b_{11}b_{22})h_{12,t-1} + b_{21}b_{22}h_{22,t-1} \tag{4.31}$$

$$h_{21,t} = c_{21}c_{11} + a_{11}a_{21}\varepsilon_{1,t-1}^2 + (a_{12}a_{21} + a_{11}a_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{12}a_{11}\varepsilon_{2,t-1}^2 + b_{11}b_{21}h_{11,t-1} + (b_{12}b_{21} + b_{11}b_{22})h_{21,t-1} + b_{21}b_{22}h_{22,t-1} \tag{4.32}$$

$$h_{22,t} = c_{22}^2 + a_{12}^2\varepsilon_{1,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^2\varepsilon_{2,t-1}^2 + b_{12}^2h_{11,t-1} + 2b_{12}b_{22}h_{12,t-1} + b_{22}^2h_{22,t-1} \tag{4.33}$$

From Equations (4.26) through to (4.33), *C* (c_{11}, c_{12}, c_{21} and c_{22}) refers to the matrix of the triangular coefficients in which c_{12} is 0 to ensure the positive definiteness of H_t. Matrices *A* (a_{11}, a_{12}, a_{21} and a_{22}) and *B* (b_{11}, b_{12}, b_{21} and b_{22}) demonstrate that conditional variances are dependent on their own lagged values and lagged return shocks by estimating the ARCH and GARCH effects, respectively.

In regard to this study, a_{11} represents the coefficient of the ARCH effect from its Saudi stock index (IS1, IS2, IS3, MS or CS). Coefficient a_{12} is the shock information from the Saudi market to the global index (Brent, WTI or S&P 500). Then, a_{21} represents the other direction of the overall shock information: from global market index to Saudi index. Coefficient a_{22} captures the impact of prior shocks from each global indices on its own current conditional variance.

Similar to the previously described process, b_{11} represents the coefficient of the GARCH effect from the Saudi index and b_{12} measures the volatility spillover from the Saudi stock market to the global index (Brent, WTI or S&P 500). In addition, coefficient b_{21} measures the volatility spillover in the other direction: from the global index to the Saudi market. Finally, the coefficient b_{22} captures the current volatility spillover from the past value of the global indices.

Table 4.6: Specifications summary for *A* and *B* matrix parameters according to the bivariate GARCH-BEKK equation

Coefficient	Interpretation	Influence Direction
	Directional past information shocks to the current index return	
a_{11}	Overall information shock (ARCH effect) from its own previous day's returns of the Saudi stock index (IS1, IS2, IS3, MS or CS).	Saudi market→Saudi market
a_{12}	Overall information shock (ARCH effect) from Saudi market to global index (Brent, WTI or S&P 500).	Saudi market→global market
a_{21}	Overall information shock (ARCH effect) from global market index to Saudi index.	Global market→Saudi market
a_{22}	Overall information shock (ARCH effect) from its own previous day's value of the global index (Brent, WTI or S&P 500).	Global market→global market
	Directional past volatility spillover effect to the current index volatility	
b_{11}	Volatility spillover (GARCH effect) from its past for the Saudi stock index (IS1, IS2, IS3, MS or CS).	Saudi market→Saudi market
b_{12}	Volatility spillover (GARCH effect) from Saudi stock index (IS1, IS2, IS3, MS or CS) to global index (Brent, WTI or S&P 500).	Saudi market→global market
b_{21}	Volatility spillover (GARCH effect) from global index (Brent, WTI or S&P 500) to Saudi market (IS1, IS2, IS3, MS or CS).	Global market→Saudi market
b_{22}	Volatility spillover (GARCH effect) from previous day of global index (Brent, WTI or S&P 500) on its current value.	Global market→global market

Source: Author's own elaboration.

As shown in Table 4.6, the significance of a_{12} reveals evidence of a shock spillover between the global index and the Saudi stock index and the significance of b_{12} indicates evidence of a volatility spillover from the global index to the Saudi index. Assuming that

a_{12} = b_{12} = 0, this indicates no volatility spillover effect from the Saudi index (IS1, IS2, IS3, MS or CS) to the global index (Brent, WTI or S&P 500). However, when a_{21} = b_{21} = 0, this reveals no evidence of a volatility spillover effect from the global index to the Saudi stock index.

Assuming a bivariate BEKK standard normal distribution of the error terms, the parameters of the bivariate GARCH modelling are estimated by maximising the log likelihood function:

$$L(\emptyset) = -T\text{In}(2\pi) - \frac{1}{2}\sum_{i=1}^{T}(In|H_t| + \varepsilon_t' H_t^{-1}\varepsilon_t) \tag{4.34}$$

where T is the number of conditional mean equations and ε_t is the T vector of mean equation residuals. Relevantly, the BFGS algorithms, by Broyden, Fletcher, Goldfarb and Shanno, are deployed as a maximisation procedure for obtaining the initial condition and final parameter estimations of the variance and covariance matrices.

4.15 Volatility Spillover and Link to Portfolio Management

The major focus of this thesis is returns volatility and the volatility spillover between Saudi stock indices and global indices (oil and US stock markets) as were previously estimated through bivariate GARCH approaches. Therefore, it is expected that these have implications for the portfolio-management decisions of investors in Saudi Arabia, especially in terms of the selection of optimal weights and hedging ratios within portfolios.[25] Therefore, this study aimed to attain a comprehensive understanding of the ways that the financial (modernising) reforms program announcements have affected Saudi stock market

[25] Employing bivariate GARCH estimations can help to provide more effective hedge recommendations than other methods (Kroner & Sultan 1993; Myers 1991; Olson et al. 2017; Park & Switzer 1995).

investors, weighted portfolios and hedging ratios by using the bivariate GARCH model (see section 4.14.3.1).

It is vital to investigate multiple segments of the Saudi stock market according to IFPs because liberalising financial reforms are expected to facilitate foreign direct investment. Local investors adhere to investment strategies according to their social norms (IFPs) whereas foreign investors may have independent investment strategies. This means that the effect of the reforms differs for segments of the market. Further, it is expected that volatility in oil prices (Brent and WTI) or in the US stock market (S&P 500) interacts differently with the three classes of stocks in Saudi Arabia. Therefore, three groups of stocks have disparate levels of risks. As a result, obtaining optimal weights and hedge ratios is expected to reveal policy insights and recommendations about the ways to use them in a strategic investment plan.

4.15.1 Optimal Weights

Mathematically, the portfolio weights are obtained from the results of the bivariate GARCH-BEKK. This GARCH model produces the components of the variance-covariance matrix, as in Equation (4.25).

Portfolio weights are a direct function of the elements of H_t. If an element of H_t changes, the weight changes correspondingly. This illustrates the investment behaviour to restructure a portfolio according to the changing risk patterns from an oil price or a global stock market index.

$$w_{.} = f\left(h_{ij}\right) \tag{4.35}$$

To determine the optimal portfolio weights of two assets (one of the five stock indices as classified under three IFP categorisation and one for oil prices, Brent and WTI, or a S&P 500 index), Kroner and Ng's (1998) method was used, as is illustrated in Equation (4.36):

$$w_{L,G,t} = \frac{h_{22t}^{G} - h_{12t}^{L,G}}{h_{11t}^{L} - 2h_{12t}^{L,G} + h_{22t}^{G}} \tag{4.36}$$

In Equation (4.36), $w_{L,G,t}$ represents the optimal portfolio of (G = oil market, Brent and WTI, or global S&P 500) relative to the risk of the assets in the Saudi stock market (L = IS1, IS2, IS3, MS or CS) at the present time (*t*) and (h_{11t}, h_{12t} *and* h_{22t}) represent the conditional variance-covariance that is obtained from Equation (4.25). According to the assumptions of a mean-variance utility function, the optimal portfolio weights of the assets in an oil market or a global stock index portfolio are given as:

$$w_t = \begin{cases} 0, & if \quad w_t < 0 \\ w_t, & if \quad 0 \le w_t \le 1 \\ 1, & if \quad w_t > 1 \end{cases} \tag{4.37}$$

Kroner and Ng (1998) suggest that the optimal weight of a portfolio contains one Saudi index and one other global index that is perceived to be $1 - w_t$. Then, a comparative test is performed to examine the hypotheses of the effect of the liberalisation and modernising reforms (pre and post) among the three Saudi stock categories. The null hypothesis is as follows:

H_0: The selection of an optimal portfolio varies among the five assets indices that apply IFPs before and after the liberalisation reform announcements.

4.15.2 Hedging Ratios

This section describes the hedging ratio applications' link to the study context. The hedging ratio is employed to measure of an index position to the overall equity risk exposure. It is essential to employ the least variance hedge ratio because this strategy's purpose is to minimise the value variance of the selected position (Kumar 2014). As is well understood, for investors to effectively hedge a position, the proper hedging ratio is vital. The hedging ratio is estimated by multiplying the correlation coefficient between actual index swings and predicted index returns. To calculate optimal hedge ratio, the process considers the quantities of both the spot asset and the hedging asset.

Nonetheless, to mitigate the risk to a portfolio, Kroner and Sultan (1993) demonstrated that an investor minimises the risk through a shorting strategy for β^* of the global index in every $1 long in the Saudi index portfolio where the hedging ratio (risk-minimising) is provided as:

$$\beta^*_{L,G,t} = \frac{h_t^{G,L}}{h_t^L} \tag{4.38}$$

where $h_t^{G,L}$t is the covariance metric of the global index returns and the Saudi index returns and h_t^G is the variance metric of the global index returns. Equation (4.38) illustrates the risk for one Saudi stock index and one global index (S&P 500, Brent or WTI) that hold to a minimum if an ownership of any $1 may be hedging for shorting position of $\beta^*_{L,G,t}$ of $1 in the Saudi stock index.

The objective of the optimal hedging ratio is to minimise the value variation of a position. By estimating the optimal portfolio weight and the hedge ratio, this thesis aimed to contribute to the knowledge of the existing literature. According to Olson et al. (2014, 2017), the purpose of this technique is to identify the impact and the consequences of certain dynamics within the market conditions.

4.16 Summary

This chapter outlined the methodological framework for the ways that this study intended to answer the questions that have been asked to address the identified gap in the existing literature. The purpose of this study was to quantify the impact of the Saudi financial reforms on the stock market by taking IFPs into account. Therefore, it was essential to begin the chapter by describing and justifying the selection of the data that was used for this purpose. The chapter then described the techniques that were employed to estimate the returns and the volatility of the chosen indices. These methods are used to establish the empirical investigations that are adopted by the study.

The chapter then presented a check on descriptive statistics, including widely used techniques such as mean, standard deviation, skewness, kurtosis, maximum and minimum and the Jarque–Bera test. Next, risk-adjusted performance measurements for the Saudi stock market indices were outlined. Moreover, stationarity tests (ADF, PP and KPSS) were described to check the unit root innovation within the selected time series. Further, the chapter considered the multicollinearity and Granger causality tests between the indices (time series) to avoid any issues when conducting the volatility spillover investigation. Then, an LM test was conducted to check the existence of the ARCH effect (clustering) within the indices series, which is required before conducting the next phases of the study (volatility modelling and volatility spillover investigation).

Furthermore, modelling the returns volatility of the selected Saudi stock indexes was conducted by using the GARCH family framework. By employing the univariate

GARCH (1,1) model in addition to the EGARCH (1,1) and the GJR-GARCH (1,1), the study can capture the various dimensions of the Saudi stock indices' returns volatility, such as symmetrical and asymmetrical effects, volatility persistence and half-life perspectives. The goal of using these techniques and statistical models for the full period and for the subperiods (before and after the reforms) was to provide empirical insights into the ways that the financial reforms have affected the Saudi stock market in regard to volatility and its innovations.

Then, the chapter investigated the volatility spillover between the Saudi stock indices and the global oil markets, such as Brent and WTI, and the US stock market (S&P 500). This spillover investigation was conducted by using three statistical methods, namely, the ARMA-GARCH model, the CCF test and the bivariate GARCH (BEKK) models. The objective of implementing these multiple approaches was to identify any variation in the volatility spillover behaviour between the Saudi stock market, which includes three classes of indices that are categorised according to IFPs, and the global markets before and after the reform period. Finally, this chapter concluded the volatility spillover investigation by presenting the implications for the portfolio. To provide policy insights for portfolio managers, the optimal weight and the hedge ratio were estimated by using Kroner and Ng's (1998) and Kroner and Sultan's (1993) techniques, respectively.

CHAPTER 5: THE PRELIMINARY ANALYSIS

5.1 Introduction

This chapter presents the preliminary analyses for the data collected through the BT to serve the purpose of this thesis. First, the data descriptive statistics are summarised and characterised to obtain the data (five stock indices from the Saudi stock market that are categorised to address IFPs and three global markets, namely, Brent, WTI and S&P 500). According to Creswell (2009), descriptive statistics commonly identify central tendency, variability and data distribution. The descriptive statistics contribute to providing fundamental knowledge about the data and helping to obtain more advanced empirical analysis and to enhance the interpretation of the results (Hair et al. 2014).

Second, an analysis of the Saudi stock market's risk-adjusted performance for three groups of Saudi stock indices is created to address IFPs. The stock market's performance is evaluated using a variety of risk-adjusted performance indicators, including the Sharpe ratio (SR), the Treynor ratio (TR), the value at risk (VaR) and the conditional value at risk (CVaR).

Third, the chapter determines the stationarity of the obtained data. The augmented Dickey–Fuller (ADF), the Phillips–Perron (PP), and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) tests are used to conduct the unit root test. Furthermore, testing for multicollinearity and Granger causality is performed before the volatility investigations are conducted.

Finally, the chapter shows the estimation of the univariate GARCH models, including symmetrical and asymmetrical GARCH. The study examines the full sample period (04 January 2010–29 June 2021) and two subsample periods for before and after the introduction of the Saudi financial reforms program in mid-2015 and compares the analysis's findings before and after 2015.

5.2 Descriptive Statistics

This section presents the descriptive statistics of eight indices. The indices consist of five Saudi stock indices that are categorised by IFPs (three Islamic stocks indices, one mixed stocks index and one non-Islamic stocks index), two external global oil indices (Brent and WTI) and the US stock market index (S&P 500). To evaluate the selected indices, the study uses the daily closing prices returns from 04 January 2010 to 29 June 2021 as the full sample period (2,994 observations). Then, the full sample is split into two subperiods on 6 May 2015 to consider the beginning of the implementation of the liberalisation reforms period in Saudi Arabia. Thus, Table 5.1 summarises the statistics for three categories: one for the full sample and the others for the pre reforms period (1,390 observations) and the post reforms period (1,604 observations).

Table 5.1: Descriptive statistics summary

		Mean	Median	Maximum	Minimum	Standard deviation	Skewness	Kurtosis	Jarque–Bera	Observation
Full sample	**IS1**	0.0197	0	9.0511	−15.9774	1.1184	−2.5506	40.2533	176,375.5	2,994
	IS2	0.0353	0	9.6709	−16.0837	1.1175	−1.7328	32.8368	112,554.9	2,994
	IS3	0.0212	0	8.5913	−15.9315	1.0345	−1.9252	39.6461	169,381.1	2,994
	MS	0.0197	0	11.1428	−16.7554	1.1235	−1.8846	36.3631	140,631.1	2,994
	CS	0.0325	0	11.2201	−16.8542	1.1357	−1.7956	35.1979	130,937.5	2,994
	Brent	0.0164	0.0106	31.9634	−28.2206	2.5822	0.2338	33.5831	116,708.8	2,994
	WTI	0.0102	0.0537	19.0774	−27.5752	2.1623	−0.3319	18.2516	29,073.08	2,994
	S&P 500	0.0461	0.0415	8.9683	−12.7652	1.0758	−0.8702	20.0336	36,573.04	2,994
Pre reforms period	**IS1**	0.0324	0	9.0511	−7.4104	1.0101	−0.5154	21.2239	19,296.27	1,390
	IS2	0.0445	0	9.6709	−8.1208	1.0493	−0.3822	21.1472	19,106.94	1,390
	IS3	0.0270	0	8.5913	−6.9823	0.8127	−0.3881	28.0354	36,335.36	1,390
	MS	0.0328	0	11.1428	−7.5468	1.0467	−0.1418	24.5890	26,998.75	1,390
	CS	0.0435	0	11.2201	−7.5943	1.0554	−0.0877	24.0907	25,764.03	1,390
	Brent	−0.0233	0	8.9454	−10.7942	1.8042	−0.2460	6.455871	705.7245	1,390
	WTI	−0.0135	−0.0090	7.5633	−8.9633	1.6306	−0.1090	5.809593	459.9351	1,390
	S&P 500	0.0449	0.0425	4.6317	−6.8958	0.9799	−0.4674	7.845339	1,410.329	1,390
Post reforms period	**IS1**	0.0087	0	7.8583	−15.9774	1.2046	−3.5402	46.64758	130,675.4	1,604
	IS2	0.0274	0	7.7389	−16.0837	1.1737	−2.5524	38.63689	86,619.21	1,604
	IS3	0.0161	0	8.0287	−15.9315	1.1940	−2.2251	36.46844	76,186.00	1,604
	MS	0.0083	0	7.1208	−16.7554	1.1862	−2.8993	41.62443	101,952.2	1,604
	CS	0.0230	0	7.4899	−16.8542	1.2011	−2.7772	40.00593	93,585.97	1,604
	Brent	0.0508	0.0632	31.9634	−28.2206	3.1026	0.2716	29.43696	46,730.41	1,604
	WTI	0.0306	0.1211	19.0774	−27.5752	2.5348	−0.3738	17.19937	13,512.44	1,604
	S&P 500	0.0472	0.0393	8.9683	−12.7652	1.1527	−1.0729	24.83646	32,175.90	1,604

Note: IS1: First Islamic Stock Index Returns, IS2: Second Islamic stock index returns, IS3: Third Islamic stock index returns, MS: Mixed Islamic stock index returns, CS: Confidential stock index returns, Brent: Oil Brent index returns, WTI: Oil West−Texas intermediate returns, S&P 500: US stock market index returns. This study uses a time frame for the data (from 4 January 2010 to 29 June 2021) to maintain the maximum efficacy of outcomes given that the financial reforms that are being investigated were announced in the middle of the indicated period.

5.2.1 Full Sample Period (from 4 January 2010 to 29 June 2021)

The highest averages (means) of the daily indices' returns during the full sample period are S&P 500 (4.61%), IS2 (3.53%), CS (3.25%), IS3 (2.12%), IS1 (1.97%), MS (1.97%), Brent (1.64%) and WTI (1.02%). Unlike the findings of Arouri et al. (2011) and Jouini (2013), all the Saudi stock market indices recorded positive returns. This inconsistency may be attributable to the research sample period given that Arouri et al. (2011) and Jouini (2013) conducted their analyses in the midst of the GFC of 2007 to 2009. This conclusion is confirmed by Alsharif (2020) given that he included more recent returns period (2000–2019) in his analysis and observed 0.03% as the average return for the Saudi stock market.

Moreover, the highest standard deviation that is reported in Table 5.1 is seen in the full sample that belongs to the oil markets Brent (2.58%) and WTI (2.16%), which implies that the risk (standard deviation) in the oil market is higher than in the stock markets (Alsharif 2020; Arouri et al. 2011; Jouini 2013). Meanwhile, of the five standard deviations for the Saudi indices, the highest is for CS (1.13%), followed by MS (1.12%), IS1 (1.11%), IS2 (1.11%) and IS3 (1.03%). Furthermore, the S&P 500 has a standard deviation of (1.07%).

In addition, Table 5.1 shows the maximum and minimum values of the indices returns for the full sample period. The highest maximum values for the oil indices returns are Brent (31.9634) and WTI (19.0774), followed by CS (11.2201), MS (11.1428), IS2 (9.6709), IS1 (9.0511) and IS3 (8.5913) respectively. The S&P 500 maximum value for all the indices returns comes in eighth place with (8.9683). Meanwhile, the lowest minimum values of daily returns in the oil sector are Brent (−28.2206) and WTI (−27.5752). The highest minimum value in S&P 500 is (−12.7652). For the Saudi indices returns, the lowest are CS (−16.8542), MS (−16.7554), IS2 (−16.0837), IS1 (−15.9774) and IS3 (−15.9315).

In line with other studies that have been conducted in Saudi Arabia by Arouri et al. (2011), Jouini (2013), Jouini and Harrathi (2014), Ashfaq et al. (2019) and Alsharif (2020), the skewness of the Saudi daily indices returns is negative for all the data sets except the Brent crude oil return, which suggests that the asymmetric tail goes more towards negative values than positive values. Similar to Naifar (2016), Table 5.1 also presents a leptokurtic kurtosis (> 3) outcome that has all positive values for all data series. Therefore, the results demonstrate that the distributions of the indices series are fat-tailed, unlike the normal distribution. Moreover, the outcomes of the Jarque–Bera (1981) normality test in Table 5.1 are significant at 1%, which confirms that all the data series' daily returns are not normally distributed.

5.2.2 Pre Reforms Period and Post Reforms Period

One of the main purposes of this study was to investigate the impact of the liberalisation reforms that occurred in the Saudi economy. Therefore, it is necessary to identify the date of the beginning of these reforms (6 May 2015) to establish comparative data series outcomes: one for the pre reforms period and another for the post reforms period. This section summarises the descriptive statistics to address these categories.

Table 5.1 shows the overall changes in the indices' returns averages. The values of the mean (average) for the pre reforms period (6 January 2010 to 4 May 2015) are IS1 (3.23%), IS2 (4.45%), IS3 (2.70%), MS (3.28%), CS (4.35%), Brent (−2.33%), WTI (−1.35%) and S&P 500 (4.49%). However, the averages of the returns for the indices IS1, IS2, IS3, MS and CS decreased for the post reforms period (6 May 2015 to 29 June 2021) while the average returns of Brent, WTI and S&P 500 increased after the reforms period.

Further, Table 5.1 shows the same changes for the maximum and minimum returns values, except for the minimum values of Brent, WTI and S&P 500, which show a decline.

Table 5.1 indicates an increase in the risk (standard deviations) for the post reforms period for all the indices returns. The standard deviations are seen in the pre reforms sample as IS1 (101.01%), IS2 (104.93%), IS3 (81.27%), MS (104.67%), CS (105.54%), Brent (180.42%), WTI (163.06%) and S&P 500 (97.99%) although it increases to IS1 (120.46%), IS2 (117.37%), IS3 (119.40%), MS (118.62%), CS (120.11%), Brent (310.26%), WTI (253.48%) and S&P 500 (115.27%).

The skewness of the daily indices returns is negative for all the variables in the pre reforms period. Further, the negative skewness exists in the post reforms sample, except for Brent, which, similar to the full sample outcomes, indicates that the asymmetric tail goes more towards negative values than positive values. The descriptive statistics in Table 5.1 present leptokurtic kurtosis outcomes that have all positive values for all the data series. This means that it may be concluded that the distributions of the indices returns are fat-tailed. Furthermore, in the full sample period in Table 5.1, the Jarque–Bera (1981) test significantly (at 1%) rejects the null hypothesis of a normal distribution for all the study indices' daily returns for the pre reforms and post reforms periods.

In order to assess the statistical significance of the change in the mean of the two periods, a t-test was conducted on the pre and post reform periods. The null hypothesis of this test assumes that the means of the two subsamples are equal. The results of a t-test conducted on the pre- and post-reform periods of Saudi stock indices, shown in Table 5.2, indicate that the change in the mean value between the two periods is statistically significant at 1%, except for IS1. Therefore, the t-test rejects the null hypothesis of equal means.

Table 5.2: Results of *T*-test to compare two periods' means

Index	*T*-test to compare two periods' means
IS1	1.2622
IS2	4.4813***
IS3	8.4401***
MS	3.5282***
CS	3.7219***

Note: ***, ** and * are significant at the 1%, 5%, 10% level, respectively. The null hypothesis: the mean for the pre reforms period is equal to the mean for the post reforms period.

5.3 Market Risk-Adjusted Performance Indicators

This study examines the performances of five stock indices for the full sample period and focuses on their performances before and after the financial reforms period. The stock market performance investigation includes SR, TR, VaR and CVaR measurements.

5.3.1 Sharpe Ratio

The SR by Sharpe (1966) is widely used as a measure of risk-adjusted performance for stock markets (Hodoshima 2018; Suryadi, Endri & Yasid 2021). Sharpe (1966) provided an indicator for performance of risk-adjusted that estimates the magnitude of excess return that is counted for total risk of an asset over the risk-free rate in a particular timeframe. When comparing the indices outcomes, a higher SR indicates a better index risk-adjusted performance and vice versa. In addition, it is critical to exclude outliers (abnormal returns) when performing the SR to improve the outcome's accuracy.[26]

Table 5.3 and Figure 5.1 present the SR for the Islamic stock indices (IS1, IS2 and IS3), the mixed stock index and the non-Islamic stock index for the full, pre reforms and post reforms periods. It shows that the Islamic indices, except IS3, outperform the other Saudi indices during the full, pre reforms and post reforms periods. However, the mixed and the

[26] According to Singhal (2016), abnormal returns (outliers) could cause increase the standard deviation (risk) as the denominator more than the value of the numerator in the equation. Therefore, it reduces the outcomes (ratio).

non-Islamic indicators (MS and CS) ranked third and fourth among these indicators during the full and subsamples periods. Further, Table 5.3 shows similar SR values between the stocks indices that have more relaxed Islamic ideologies and the SR during the full sample for MS and CS are 0.0820 and 0.0848, respectively. This findings are similar to Ahmad and Alsharif (2019) and Alsharif and Ahmad (2021).

Table 5.3: Sharpe ratio for indices in Saudi stock market (from 04 January 2010 to 29 June 2021)

Index	Full Period	Pre Reforms Period	Post Reforms Period	Change %
IS1	0.0978	0.1359	0.0665	51%
IS2	0.1164	0.1602	0.0816	49%
IS3	0.0008	0.0069	−0.0038	155%
MS	0.0820	0.1253	0.0486	61%
CS	0.0848	0.1305	0.0490	62%

According to Table 5.3, the SR for all the Saudi stock indices during the pre-reforms period performs way better than during the post-reforms period. The decline of SR means that the return of the Saudi stock indices is less compared to the risk taken to achieve that return. This could be due to changes in the indices risk-adjusted returns or the risk-free rate. Table 5.3 shows that the sharp decline in the SR for the Islamic indices, except IS3, is approximately 51.06% and 49.06% for IS1 and IS2, respectively. However, the decline in the SR for the Islamic indices during the post reforms period is lower than the decline for MS and CS, which are 61.21% and 62.45%, respectively. The decline in Islamic stock indices has been lower than the decline of IFP-conflicting (SR) stocks in their conventional counterparts. Despite this, Islamic stocks show higher SR compared to conventional indices, which is inconsistent with the findings of Banani and Hidayatun (2017), who suggest that SR is lower for Islamic stocks in the Indonesian market.

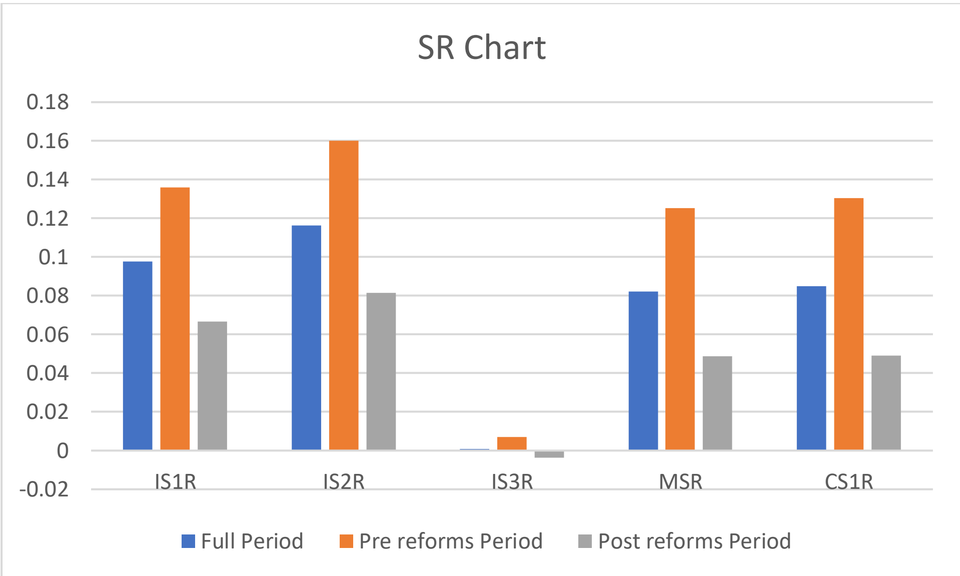
On the other hand, Table 5.4 shows that SR has increased for all of the Saudi indices during the COVID-19 period and reached the level of SR in the pre-reform period.

According to Goldstein et al. (2021), a large increase in SR is required by financial markets in case of a major event is large such as COVID-19. Furthermore, financial markets signal mixed Sharpe ratio outcomes (Nieto & Rubio 2022). However, the results on Table 5.4 are consistent with the explanation provided by Schneider et al. (2020), which suggests that the sharp decline in stock prices caused an increase in return, which also reflects on the SR.

Table 5.4: Sharpe ratio for indices in Saudi stock market (from 15 May 2015 to 29 June 2021)

Index	Post Reforms, Pre Covid-19	Post Reforms, During Covid-19
IS1	0.0347	0.1807
IS2	0.0536	0.1882
IS3	−0.0383	0.1325
MS	0.0168	0.1697
CS	0.0143	0.1744

Figure 5.1: Sharpe ratio measures for Saudi stock indices



Note: this chart is drawn by the researcher.

5.3.2 Treynor Ratio

This study also uses the Treynor (1965) ratio to evaluate the market index performance. TR as a method is similar to that of SR in that the two methods indicate the equity performance of the risk-adjusted equity. However, the TR incorporates systematic risk instead of global risk, as in SR estimations. As with SR, a greater value of TR indicates that the index outperforms the other assets and vice versa.

Table 5.5 summarises the TR outcomes for the Islamic stock indices (IS1, IS2 and IS3), the mixed stock index and the non-Islamic stock index for the full period, the pre reforms phase (from 04 January 2010 to 05 May 2015) and the post reforms phase (from 06 May 2015 to 29 June 2021). The findings for all the indicators are comparable to those for the SR in the post reforms sample in terms of the reduction in the TR values. However, as in Ahmad and Alsharif (2019) and Alsharif and Ahmad (2021), the gap in the TR values between the Islamic indices, excluding IS3, the mixed stocks and the non-Islamic indices narrows throughout full study periods.

Table 5.5: Results of performance measurement according to Treynor ratio

Index	Full Period	Pre Reforms Period	Post Reforms Period
IS1	0.0319	0.0422	0.0226
IS2	0.0469	0.0597	0.0349
IS3	0.0002	0.0014	−0.0011
MS	0.0333	0.0463	0.0212
CS	0.0348	0.0490	0.0215

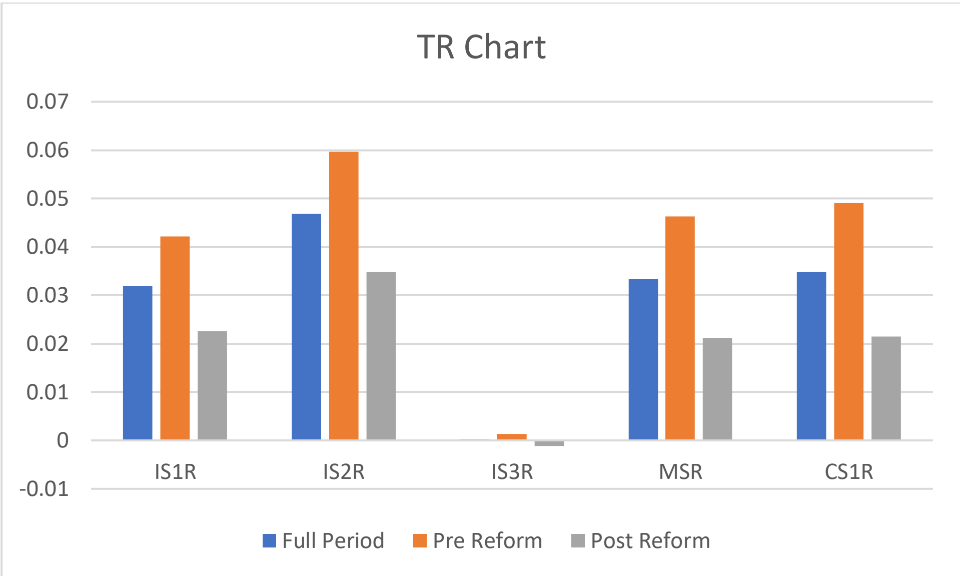
For the post reforms period, the Islamic indices (IS1 and IS2) have higher positive values than the other stocks indices, which means that the Islamic stocks, except IS3, outperform the mixed and the non-Islamic stocks. Table 5.5 confirms on the SR outcomes that is TR and SR for all Saudi stock indices are underperformed during the financial reforms period, which may be explained by the oil price decline and its effects on the Saudi economy.

Furthermore, Table 5.6 shows increase in the TR of the Saudi indices which confirms the results of SR in previous section.

Table 5.6: Results of performance measurement before and after Covid-19 period according to Treynor ratio

Index	Pre Covid-19	During Covid-19
IS1	0.0117	0.0625
IS2	0.0231	0.0780
IS3	−0.0113	0.0357
MS	0.0074	0.0703
CS1	0.0063	0.0758

Figure 5.2: Chart comparing Treynor ratio between selected Saudi indices



Note: this chart is drawn by the researcher.

5.3.3 Value at Risk and Conditional Value at Risk

This research applies VaR to examine risk-adjusted performance in regard to the returns of three stock indices categories, based on IFP, for the full period (4 January 2010 to 29 June 2021), pre and post the financial reforms program was introduced in Saudi Arabia in June 2015. The purpose of applying VaR technique is to estimate the probability of losing value over a specific period.

Table 5.7 presents the VaR and the CVaR results for five Saudi stock indices that are categorised as the Islamic stock indices (IS1, IS2 and IS3), the mixed stock index (MS) and the non-Islamic stock index (CS) for the full period, the pre reforms phase (from 04 January 2010 to 05 May 2015) and the post reforms phase (from 06 May 2015 to 29 June 2021) with a 95% confidence level.

Table 5.7: Results of performance measurement according to VaR and CVaR

Index	VaR			CVaR	
	Full Period	**Pre Reforms**	**Post Reforms**	**Pre Reforms**	**Post Reforms**
IS1	0.7145	0.6998	0.7181	0.0269	0.0006
IS2	0.8739	0.8635	0.8549	0.0361	0.0034
IS3	0.5460	0.4581	0.5689	0.0040	0.0156
MS	0.8656	0.8137	0.8410	0.0237	0.0095
CS	0.8424	0.8450	0.8292	0.0250	0.0104

Note: VaR refers to the value at risk and CVaR is the conditional value at risk.

The overall outcomes of VaR present high risk coefficients for all the Saudi stock indices for the full and pre and post reforms periods. A higher risk coefficient is reported for the mixed and the non-Islamic stocks, above the Islamic stocks, except IS2 (0.8739), for all the study periods. Further, Table 5.7 shows a slight increase in the risk coefficients for IS1, IS3 and MS and a slight decrease for IS2 and CS in the post reforms period in Saudi Arabia.

The CVaR analysis results in Table 5.7 reveal a high loss in the Saudi stock market indices. All the indicators' average risk coefficients show lower average risk coefficients during the post reforms period than in the pre reforms period. The Islamic indicators, except IS3, have the highest average risk (CVaR) for the two subperiods. Moreover, the decline in the risk exposure that estimates the potential loss in the indices during the post reforms period can be explained by the decline in oil prices or by the increase of QFIIs into the Saudi stock market.

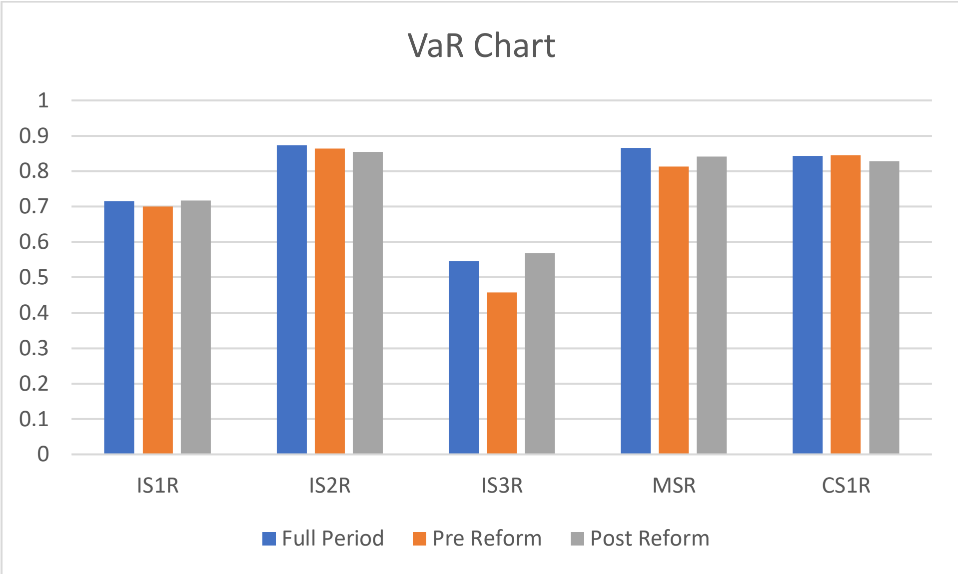
According to Table 5.8, both VaR and CVaR for all Saudi indices have increased during the COVID-19 period, except for the MS. The increase in VaR and CVaR for the Saudi indices comes in line with the China, UK, and US markets (Li et al. 2022). Li et al. (2022) explained that the increase in COVID-19 cases may cause an increase in market risk across the markets, which reflects on the VaR and CVaR. In other words, the increase in the VaR and CVaR for stock markets may be explained by the increased potential for losses caused by the uncertainty associated with the COVID-19 pandemic, as well as the changes in underlying risk factors such as interest rates and inflation that have been affected by the pandemic. Therefore, investors should consider shifting to more aggressive investments to take advantage of potential gains in the markets.

Table 5.8: Results of performance measurement according to VaR and CVaR

Index	VaR		CVaR	
	Pre Covid-19	**Post Covid-19**	**Pre Covid-19**	**Post Covid-19**
IS1	0.7164	0.7193	0.0088	0.0324
IS2	0.8429	0.9307	0.0062	0.0359
IS3	0.5679	0.5694	0.0245	0.0137
MS	0.8410	0.8129	0.0221	0.0292
CS	0.8047	0.9563	0.0234	0.0306

Note: VaR refers to value at risk and CVaR is the conditional value at risk.

Figure 5.3: Chart comparing VaR between selected Saudi indices



Note: this chart is drawn by the researcher.

5.4 Unit Root Tests

This section presents the essential preliminary analysis, which entails determining the stationarity of each index's daily returns by applying the ADF, PP and KPSS tests. The Saudi stock market and the global indices are tested for stationarity in the full and the subperiods samples. The outcomes in Table 5.9 show an agreement for all the tests of stationary data series. The ADF and PP tests are significant at 1%, which indicates that all the variables are non-stationary at all levels. Further, the KPSS method provides outcomes that are consistent with the ADF and PP tests, which indicates that all of the Saudi stock indices and global markets are stable in first differences for conducting the remaining analyses steps. These outcomes are aligned with previous studies such as Alqahtani et al. (2020).

Table 5.9: Stationarity tests results

	Level			
	Index	**ADF**	**PP**	**KPSS**
Study Sample	IS1	-21.76^{***}	-55.80^{***}	0.10
	IS2	-36.62^{***}	-55.54^{***}	0.11
	IS3	-37.32^{***}	-56.93^{***}	0.11
	MS	-36.07^{***}	-55.17^{***}	0.09
	CS	-36.03^{***}	-54.81^{***}	0.09
	Brent	-55.89^{***}	-55.86^{***}	0.13
	WTI	-54.25^{***}	-54.33^{***}	0.08
	S&P 500	-18.22^{***}	-63.42^{***}	0.05

Note: The null hypothesis for ADF and PP: "there is unit root in the data set". ***, ** and *: Levels of significance at 1%, 5% and 10%, respectively. The null hypothesis of no stationarity for the ADF and PP unit root tests is rejected if the ADF and PP test statistics are less than the critical values at 1%, 5% and 10%, respectively. Meanwhile, the KPSS test statistic of the null hypothesis of stationarity is only rejected if the results value is lower than the confidence level of 1%, 5% and 10%, respectively.

5.5 Granger Causality Test

This section presents the results of the Granger causality test (Engle & Granger 1987; Granger 1969, 1981; Granger & Hallman 1991). It is critical to consider the lag returns for the Saudi stock indices to capture the relationship between the local indices and the global indicators, whose trading hours are in the US time zone (see Table 5.10). Table 5.10 confirms the significance of the one-day lag causality from the global indices (Brent, WTI and S&P 500) to all the stock indices in Saudi Arabia at a 1% confidence level. Meanwhile, the results in Table 5.10 show no causality from the Saudi stock indices to the global markets.

Table 5.10: Results for Granger causality test

Null Hypothesis	Lag	*F*-Statistic	Probability	Result
Brent does not Granger cause IS1	1	25.5264	0.0000*	Brent causes IS1
IS1 does not Granger cause Brent	1	0.3725	0.5417	/
WTI does not Granger cause IS1	1	13.5023	0.0002*	WTI causes IS1
IS1 does not Granger cause WTI	1	0.0609	0.8052	/
S&P 500 does not Granger cause IS1	1	21.3591	0.0000*	S&P 500 causes IS1
IS1 does not Granger cause S&P 500	1	0.7566	0.3845	/
Brent does not Granger cause IS2	1	22.4407	0.0000*	Brent causes IS2
IS2 does not Granger cause Brent	1	0.1071	0.7435	/
WTI does not Granger cause IS2	1	11.8919	0.0006*	WTI causes IS2
IS2 does not Granger cause WTI	1	0.0591	0.8080	/
S&P 500 does not Granger cause IS2	1	16.7994	0.0000*	S&P 500 causes IS2
IS2 does not Granger cause S&P 500	1	0.9344	0.3339	/
Brent does not Granger cause IS3	1	26.4536	0.0000*	Brent causes IS3
IS3 does not Granger cause Brent	1	0.2156	0.6425	/
WTI does not Granger cause IS3	1	21.6715	0.0000*	WTI causes IS3
IS3 does not Granger cause WTI	1	0.02705	0.8694	/
S&P 500 does not Granger cause IS3	1	9.9273	0.0017*	S&P 500 causes IS3
IS3 does not Granger cause S&P 500	1	3.1469	0.0763	/
Brent does not Granger cause MS	1	20.4606	0.0000*	Brent causes MS
MS does not Granger cause Brent	1	0.3655	0.5456	/
WTI does not Granger cause MS	1	11.1332	0.0009*	WTI causes MS
MS does not Granger cause WTI	1	0.0279	0.8674	/
S&P 500 does not Granger cause MS	1	18.1328	0.0000*	S&P 500 causes MS
MS does not Granger cause S&P 500	1	0.4635	0.4961	/
Brent does not Granger cause CS	1	21.2825	0.0000*	Brent causes CS
CS does not Granger cause Brent	1	0.4629	0.4964	/
WTI does not Granger cause CS	1	12.0208	0.0005*	WTI causes CS
CS does not Granger cause WTI	1	0.0137	0.9068	/
S&P 500 does not Granger cause CS	1	17.8320	0.0000*	S&P 500 causes CS
CS does not Granger cause S&P 500	1	0.4582	0.4986	/

Note: (/) refer to no Granger causes between indexes return.

5.6 Multicollinearity Test

This section presents the essential preliminary analyses to test the multicollinearity within the independent variables before conducting the econometrics analyses. In the case of this study, the global indices, namely, S&P 500, WTI and Brent crude oil, have been tested for multicollinearity. Table 5.11 shows an overall strong positive correlation between the oil markets and the US stock market and vice versa. Therefore, a two-factor model (multiple regression) is estimated and discussed in the next chapter.

Table 5.11: Metrics correlation within global indices

	Brent	WTI	S&P 500
Brent	1.0000	0.8359	0.4144
WTI	0.8359	1.0000	0.3931
S&P 500	0.4144	0.3931	1.0000

5.6.1 ARCH-LM and Volatility Clustering Analysis

The outcomes of Table 5.12 and Figure 5.4 demonstrate that all the study's historical daily indices (five stock indices of Saudi stock returns, the S&P 500, Brent and WTI) exhibit volatility clustering, which implies that low volatility periods are typically followed by low volatility periods, whereas high volatility periods are typically followed by high volatility periods (Kirchler & Huber 2007). Thus, this indicates the existence of volatility clusters and an ARCH effect in the data set. These findings, as is seen in Figure 5.4, are consistent with prior studies by Mandelbrot (1963), Fama (1965) and Rydberg (2000), which assert that stock returns normally follow a non-normal distribution that is characterised by leptokurtosis, skewness and volatility clustering.

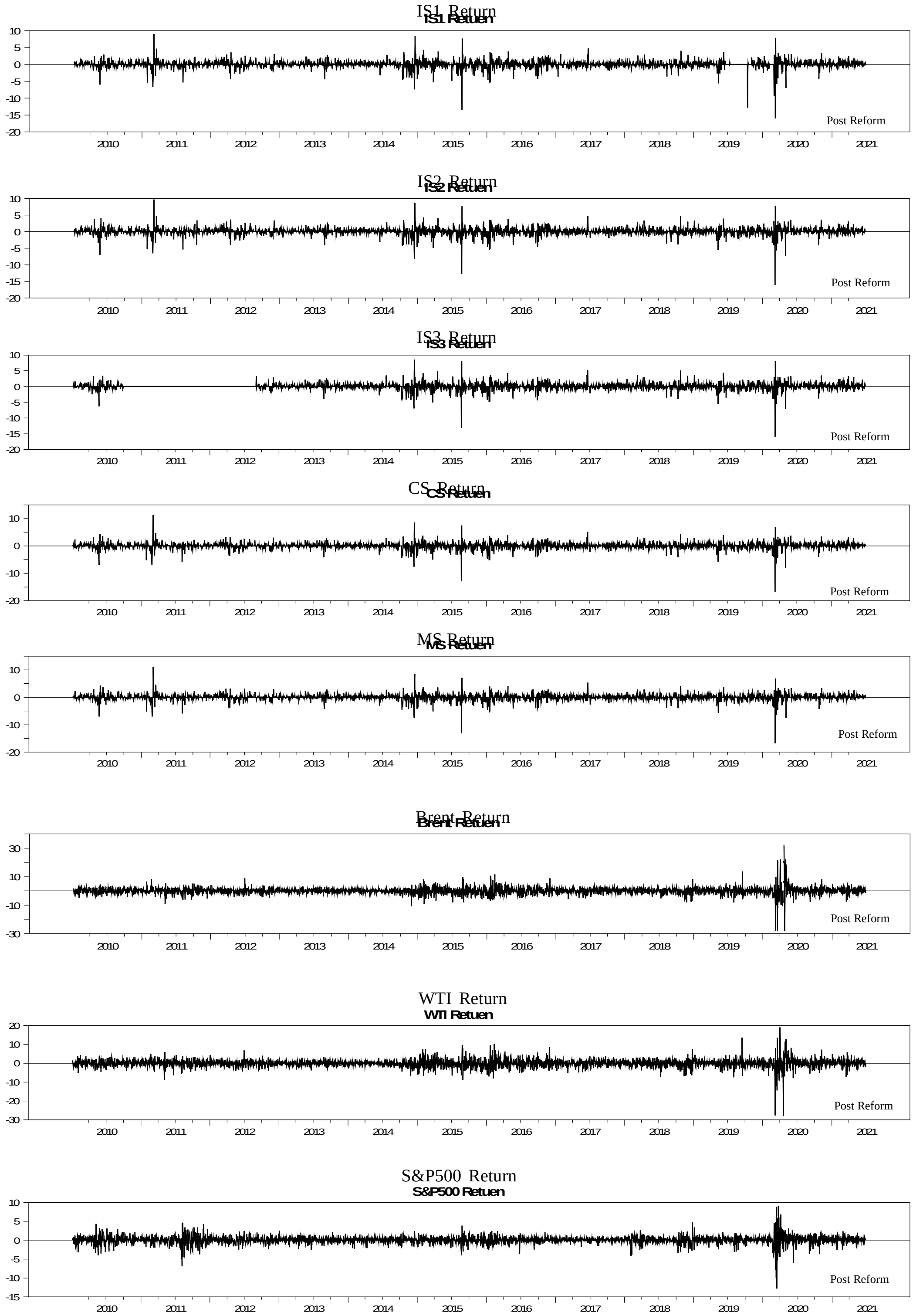
In addition, results in Table 5.12 suggest that the GARCH framework is appropriate since it shows the presence of heteroskedasticity in all indices data, which is a necessary condition for a GARCH model to be valid. In other words, the ARCH LM test rejects the null hypothesis of homoskedasticity (no ARCH effect in the residual term), which determines the presence of time-varying volatility in the selected periods for all of the Saudi stock indices, US stock market, and Brent and WTI oil indices.

Table 5.12: ARCH Effect for Saudi stock indices, US stock market, and Oil indices for full period

	ARCH LM Test			
	F-statistic		$Obs*R^2$	
Indices	**Value**	**Probability**	**Value**	**Probability**
IS1	105.4501	0.0000	101.9282	0.0000
IS2	154.7546	0.0000	147.2423	0.0000
IS3	154.0746	0.0000	146.6270	0.0000
MS	94.2680	0.0000	91.4498	0.0000
CS	100.1583	0.0000	96.9789	0.0000
Brent	284.3851	0.0000	259.8745	0.0000
WTI	162.1824	0.0000	153.9461	0.0000
S&P 500	455.7924	0.0000	395.8018	0.0000

Note: $Obs*R^2$ refers to the LM test statistic for the null hypothesis of no serial correlation.

Figure 5.4: Historical daily returns for Saudi, S&P 500, Brent and WTI stock indices (full period from 4 January 2010 to 29 June 2021, including the periods pre and post the liberalisation reforms)



In addition, Figure 5.4 indicates that all the index returns (abnormal returns) were at an all-time high towards the end of 2019, which is considered to correspond with the global COVID-19 pandemic announcement. Unlike the global S&P 500 index, Brent or WTI, the Saudi stock returns exhibit more instances of returns spikes (abnormal), such as the increase in returns at the end of 2010, another spike in returns in mid-2014 and one in early 2015. Between 2010 and 2014, abnormal returns might readily take into account the influence of the oil price fall. However, the abnormal returns behaviour in 2015 may be related to the implementation of Vision 2030 (Saudi Arabia's social economic reforms plan).

5.7 Findings from Analysis of Univariate Volatility Behaviours

This section presents the estimation outcomes of various univariate GARCH models. GARCH (1,1), EGARCH (1,1) and GJR-GARCH (1,1) are used to capture the symmetrical and asymmetrical patterns that exist within three Islamic indices' daily returns, one mixed Islamic index's daily returns, one non-Islamic index's daily returns and three external factors that are represented by Brent, WTI and S&P 500. Table 5.13, Table 5.14 and Table 5.15 show the conditional variance equations for the full sample, the pre reforms period and the post reforms period, respectively.

Table 5.13: Conditional variance equations (full sample: from 6 January 2010 to 29 June 2021)

		ω	**α**	**β**	**γ**	**LL**	**AIC**	**SC**
IS1	GARCH (1,1)	0.1015***	0.0843***	0.8264***	–	−4,180.2730	2.7948	2.8049
	EGARCH (1,1)	−0.0486***	0.0616***	0.9479***	−0.1576***	−4,077.1720	2.7267	2.7387
	GJR-GARCH (1,1)	0.5239***	−0.0432***	0.6201***	0.2675***	−4,362.5760	2.9172	2.9293
IS2	GARCH (1,1)	0.0367***	0.0921***	0.8821***	–	−4,090.5260	2.7349	2.7449
	EGARCH (1,1)	−0.0923***	0.1332***	0.9625***	−0.1415***	−3,982.4080	2.6634	2.6754
	GJR-GARCH (1,1)	0.0405***	−0.0169***	0.8946***	0.1682***	−3,981.7950	2.6630	2.6750
IS3	GARCH (1,1)	0.0018***	0.0943***	0.9250***	–	−3,319.9820	2.2204	2.2304
	EGARCH (1,1)	−0.1087***	0.1768***	0.9747***	−0.1224***	−3,208.2560	2.1464	2.1584
	GJR-GARCH (1,1)	0.0019***	0.0416***	0.9252***	0.1123***	−3,278.5740	2.1934	2.2054
MS	GARCH (1,1)	0.0412***	0.0960***	0.8756***	–	−4,113.3990	2.7502	2.7602
	EGARCH (1,1)	−0.0937***	0.1343***	0.9613***	−0.1433***	−4,006.1540	2.6792	2.6913
	GJR-GARCH (1,1)	0.0404***	−0.0104***	0.8912***	0.1647***	−0.0046	2.6831	2.6952
CS	GARCH (1,1)	0.0392***	0.0920***	0.8811***	–	−4,142.2910	2.7695	2.7795
	EGARCH (1,1)	−0.0931***	0.1361***	0.9632***	−0.1388***	−4,037.1440	2.6999	2.7120
	GJR-GARCH (1,1)	0.0402***	−0.0115***	0.8948***	0.1615***	−4,037.3290	2.7001	2.7001
WTI	GARCH (1,1)	0.0566***	0.0971***	0.8955***	–	−6,042.1260	4.0381	4.0482
	EGARCH (1,1)	−0.0846***	0.1374***	0.9856***	−0.0855***	−5,996.6640	4.0085	4.0205
	GJR-GARCH (1,1)	0.0568***	0.0273***	0.9071***	0.1074***	−6,042.1260	4.0381	4.0482
S&P 500	GARCH (1,1)	0.0382***	0.1864***	0.7812***	–	−3,688.0750	2.4662	2.4762
	EGARCH (1,1)	−0.2022***	0.2448***	0.9474***	−0.1601***	0.0139	2.4283	2.4403
	GJR-GARCH (1,1)	0.0380***	0.0506***	0.7956***	0.2,329***	−3,641.8580	2.4360	2.4480

Note: ***, ** and*: Levels of significance at 1%, 5% and 10%, respectively. ω is the constant, α is the ARCH coefficient, β is the GARCH coefficient and γ is the asymmetric coefficient. In addition, LL is the log likelihood, AIC is the Akaike information criterion and SC is the Schwarz criterion.

Table 5.14: Conditional variance equation (pre reforms period: from 6 January 2010 to 5 May 2015)

		ω	**α**	**β**	**γ**	**LL**	**AIC**	**SC**
IS1	GARCH (1,1)	0.0307***	0.0307***	0.8956***	–	−1,733.18	2.5028	2.5216
	EGARCH (1,1)	−0.1127***	0.1425***	0.9523***	−0.1568***	−1,671.91	2.4160	2.4386
	GJR-GARCH (1,1)	0.1074***	−0.0272***	0.8062***	0.1642***	−1,720.87	2.4865	2.5091
IS2	GARCH (1,1)	0.0333***	0.0767***	0.8904***	–	−1,781.77	2.5727	2.5916
	EGARCH (1,1)	−0.1082***	0.1420***	0.9532***	−0.1593***	−1,718.90	2.4836	2.5063
	GJR-GARCH (1,1)	0.1517***	−0.0277***	0.7627***	0.1214***	−1,815.94	2.6234	2.6460
IS3	GARCH (1,1)	0.0017***	0.0853***	0.9296***	–	−906.98	1.3132	1.3320
	EGARCH (1,1)	−0.1254***	0.1989***	0.9739***	−0.1188***	−867.28	1.2574	1.2800
	GJR-GARCH (1,1)	0.0018***	0.0330***	0.9264***	0.1315***	−885.73	1.2840	1.3066
MS	GARCH (1,1)	0.0393***	0.0764***	0.8822***	–	−1,778.63	2.5682	2.5871
	EGARCH (1,1)	−0.1096***	0.1375***	0.9480***	−0.1,744***	−1,714.96	2.4780	2.5006
	GJR-GARCH (1,1)	0.0421***	−0.0307***	0.8912***	0.1715***	−1,706.40	2.4657	2.4883
CS	GARCH (1,1)	0.0368***	0.0722***	0.8897***	–	−1,792.13	2.5877	2.6065
	EGARCH (1,1)	−0.1081***	0.1399***	0.9509***	−0.1647***	−1,731.87	2.5023	2.5250
	GJR-GARCH (1,1)	0.0429***	−0.0272***	0.8920***	0.1649***	−1,722.83	2.4893	2.5119
WTI	GARCH (1,1)	0.0153***	0.0489***	0.9472***	–	−2,511.57	3.6236	3.6424
	EGARCH (1,1)	−0.0671***	0.0997***	0.9907***	−0.0545***	−2,499.15	3.6071	3.6297
	GJR-GARCH (1,1)	0.0163***	0.0209***	0.9495***	0.0490***	−2,503.28	3.6131	3.6131
S&P 500	GARCH (1,1)	0.0364***	0.1357***	0.8255***	–	−1,744.05	2.5184	2.5373
	EGARCH (1,1)	−0.1232***	0.1402***	0.9447***	−0.2249***	−1,700.12	2.4566	2.4792
	GJR-GARCH (1,1)	0.0345***	−0.0563***	0.8711***	0.2922***	−1,698.60	2.4544	2.4770

Note: ***, ** and *: Levels of significance at 1%, 5% and 10%, respectively. ω is the constant, α is the ARCH coefficient, β is the GARCH coefficient and γ is the asymmetric coefficient. In addition, LL is the log likelihood, AIC is the Akaike information criterion and SC is the Schwarz criterion.

Table 5.15: Conditional variance equation (post reforms period: from 6 May 2015 to 29 June 2021)

		ω	**α**	**β**	**γ**	**LL**	**AIC**	**SC**
IS1	GARCH (1,1)	0.1612***	0.0910***	0.7915***	–	−2,392.8360	2.9880	3.0047
	EGARCH (1,1)	−3.9600***	−0.0018***	0.9819***	−0.1087***	−2,335.0340	2.9172	2.9373
	GJR-GARCH (1,1)	0.0726***	−0.0265***	0.9055***	0.1127***	−2,346.1250	2.9310	2.9511
IS2	GARCH (1,1)	0.0412***	0.1046***	0.8749***	–	−2,302.8340	2.8758	2.8926
	EGARCH (1,1)	−0.0707***	0.1083***	0.9693***	−0.1356***	−2,256.2100	2.8190	2.8391
	GJR-GARCH (1,1)	0.0419***	−0.0125***	0.8989***	0.1643***	−2,256.5850	2.8194	2.8395
IS3	GARCH (1,1)	0.0433***	0.0994***	0.8804***	–	−2,371.0790	2.9608	2.9776
	EGARCH (1,1)	−0.0626***	0.1031***	0.9695***	−0.1331***	−2,324.0480	2.9035	2.9236
	GJR-GARCH (1,1)	0.0453***	−0.0026	0.8971***	0.1521***	−2,329.7000	2.9105	2.9306
MS	GARCH (1,1)	0.0435***	0.1119***	0.8701***	–	−2,326.8910	2.9058	2.9225
	EGARCH (1,1)	−0.0772***	0.1177***	0.9692***	−0.1293***	−2,282.2470	2.8514	2.8715
	GJR-GARCH (1,1)	0.0428***	0.0009	0.8906***	0.1591***	−2,290.2880	2.8614	2.8815
CS	GARCH (1,1)	0.0406***	0.1078***	0.8754***	–	−2,339.4530	2.9214	2.9382
	EGARCH (1,1)	−0.0790***	0.1234***	0.9698***	−0.1294***	−2,296.5870	2.8693	2.8894
	GJR-GARCH (1,1)	0.0422***	−0.0016	0.8946***	0.1579***	−2,302.0150	2.8760	2.8961
WTI	GARCH (1,1)	0.1640***	0.1186***	0.8589***	–	−3,512.1480	4.3827	4.3995
	EGARCH (1,1)	−0.0687***	0.1354***	0.9786***	−0.1102***	−3,482.1270	4.3466	4.3667
	GJR-GARCH (1,1)	0.1373***	0.0205**	0.8831***	0.1439***	−3,486.4620	4.3520	4.3721
S&P 500	GARCH (1,1)	0.0410***	0.2428***	0.7334***	–	−1,935.2110	2.4177	2.4345
	EGARCH (1,1)	−0.2713***	0.3303***	0.9398***	−0.1515***	−1,913.0500	2.3913	2.4115
	GJR-GARCH (1,1)	0.0415***	0.1212***	0.7288***	0.2547***	−1,915.5230	2.3944	2.4145

Note: ***, ** and *: Levels of significance at 1%, 5% and 10%, respectively. ω is the constant, α is the ARCH coefficient, β is the GARCH coefficient and γ is the asymmetric coefficient. In addition, LL is the log likelihood, AIC is the Akaike information criterion and SC is the Schwarz criterion.

In the outcomes for the conditional variance equations that are illustrated in Table 5.13,Table 5.14 and Table 5.15, ω is the constant, α is the ARCH term and β is the GARCH term for the GARCH (1,1), EGARCH (1,1) and GJR-GARCH (1,1) models. However, γ exists only within the EGARCH (1,1) and GJR-GARCH (1,1) models to capture the asymmetric (leverage) effect.

5.7.1 Findings from Full Sample Period (2010–2021)

Table 5.13 shows a statistical significance of 1% for all the conditional variance equation elements in the full sample period. In other words, the ω, α and β in the GARCH (1,1), EGARCH (1,1) and GJR-GARCH (1,1) models for IS1, IS2, IS3, MS, CS, Brent, WTI and S&P 500 series have a significant effect (predictive power) on current returns volatility.

Further, the asymmetrical (leverage) effect through the parameter estimate γ for all the EGARCH models of all the study variables are statistically significant at the 1% level (negative value). This reveals that negative shocks predict a higher conditional variance (volatility) in the following period than positive shocks, which confirms the presence of leverage (asymmetrical) effects in the indices returns across the full sample period. The findings of asymmetrical effect existences for Islamic and conventional stocks confirms Fakhfekh et al. (2016) and Alzyadat et al. (2021).

Moreover, another asymmetrical GJR-GARCH (1,1) model confirms the EGARCH model outcomes that the coefficient for the leverage effect (γ) is significant at 1% and positive for all the indices returns volatility over the whole sample (see Table 5.13). The positive coefficient of γ shows that negative shocks (bad news) have a greater influence on conditional variance (volatility) than positive shocks (good news) of the same size.

5.7.2 Findings from Subsamples Periods

For comparative analyses purposes, the study suggests dividing the overall sample into two subsamples that aim to capture the effect of the Saudi Arabian liberalisation reforms program on Saudi stock indices returns that are categorised to address religious financial principles. As a result, every index's daily returns series is split into two series: one for the pre reforms period and the other for the post reforms period, as are illustrated in Table 5.14 and Table 5.15.

Similar results as those in Table 5.13 occur in Table 5.14, which represents the pre reform period. However, the behaviour of the conditional variance equations in Table 5.15 (post reforms period) in this study has a slight change in terms of the non-significant statistics of α (the ARCH effect) for IS3, MS and CS when modelling the volatility via the GJR-GARCH method. In addition, the significant relationship confidence level change of α in the WTI data series is identified in the GJR-GARCH case. α is significant at 1% in the pre reforms period and remains statistically significant at the 5% confidence level (see Table 5.14 and Table 5.15 for comparison).

This variation in the change of returns volatility may be explained because the estimations of the univariate GARCH models are different. The symmetrical GARCH (1,1) has limited functions because it does not include an additional dummy element in its equations like in the asymmetrical methods. Considering the outcomes of the leverage effect in the EGARCH and GJR-GARCH estimations, the study finds close values for gamma (γ) for almost all the indices returns in Table 5.14 and Table 5.15. However, the analyses of the pre and post reforms periods identify a decrease in the asymmetrical power values. This suggests that liberalising the stock market may play a role in reducing the impact of bad news on conditional variance (volatility), unlike good news of the same size. These findings suggest a similar conclusion to that by Bensethom (2021) in that liberalising the stock market may reduce the impact of bad news on conditional variance (volatility). The greater transparency and higher numbers of participants (QFIIs) associated with liberalisation can lead to a more efficient stock market and less volatility when bad news is released (Rejeb & Boughrara 2013; Li et al. 2020).

5.7.3 Volatility Persistence and Half-Life

To capture the change in the volatility persistence between the two subperiods, the volatility persistence is calculated as the sum of the ARCH effect and the GARCH effect $(\alpha + \beta)$ in the conditional variance equations for the symmetric GARCH (1,1) model. For EGARCH (1,1), β measures the volatility persistence. Meanwhile, the GJR-GARCH (1,1) model measures the persistence of volatility with $(\alpha + \beta + \frac{\gamma}{2})$.[27]

The results for volatility persistence in Table 5.16 shows an overall increase in volatility persistence for the Saudi stock indices during the financial reforms period, unlike the period before the reforms period. This outcome confirms a study by Wang and Yang (2017), which suggests that large negative returns in daily stock prices strongly influence the persistence of volatility. For example, Table 5.16 shows that the IS1 half-life indicates that a volatility shock is vital and lasted for 14.18 days in the pre reforms period. Further, the volatility shock influence increased in the post reforms period to last for 37.95 days for the EGARCH. Similarly, the GJR-GARCH indicates an increase from 4.64 days to 10.38 days. However, the symmetric GARCH (1,1) model reports a reduction in volatility

[27] For more discussions about the methods for measuring volatility persistence and half-lives, see the previous chapter.

persistence. These observations are consistent with those of earlier empirical studies (Bouri & Yahchouchi 2014; Neaime 2012).

In the comparison between Islamic and conventional stocks, the volatility persistence and half-life for the Islamic stock indices is lower than that of the other conventional indices during the post-reform period, which is in line with Fakhfekh et al. (2016) findings. However, the other IS2, IS3, MS, and CS indices show similar levels of volatility persistence and half-life increase while IS1 is the only index that showed a decrease in volatility and half-life during the post-reform period.

Table 5.16: Volatility persistence and half-lives of Saudi and global indices

		Full Sample		**Pre Reform Period**		**Post Reform Period**	
Index	**Model Type**	**VP**	**HL**	**VP**	**HL**	**VP**	**HL**
	GARCH (1,1)	0.9107	7.41	0.9263	9.05	0.8825	5.55
IS1	EGARCH (1,1)	0.9479	12.95	0.9523	14.18	0.9819	37.95
	GJR-GARCH (1,1)	0.7107	2.03	0.8611	4.64	0.9354	10.38
	GARCH (1,1)	0.9742	26.52	0.9671	20.72	0.9795	33.46
IS2	EGARCH (1,1)	0.9625	18.14	0.9532	14.46	0.9693	22.23
	GJR-GARCH (1,1)	0.9618	17.80	0.7957	3.03	0.9686	21.73
	GARCH (1,1)	1.0193	36.26	1.0149	46.87	0.9798	33.97
IS3	EGARCH (1,1)	0.9747	27.05	0.9739	26.21	0.9695	22.38
	GJR-GARCH (1,1)	1.0230	30.48	1.0252	27.85	0.9706	23.23
	GARCH (1,1)	0.9716	24.06	0.9586	16.39	0.982	38.16
MS	EGARCH (1,1)	0.9613	17.56	0.9480	12.98	0.9692	22.16
	GJR-GARCH (1,1)	0.9632	18.49	0.9463	12.55	0.9711	23.64
	GARCH (1,1)	0.9731	25.42	0.9619	17.84	0.9832	40.91
CS	EGARCH (1,1)	0.9632	18.49	0.9509	13.77	0.9698	22.60
	GJR-GARCH (1,1)	0.9641	18.96	0.9473	12.79	0.9720	24.41
	GARCH (1,1)	0.9926	93.32	0.9961	177.38	0.9775	30.46
WTI	EGARCH (1,1)	0.9856	47.79	0.9907	74.18	0.9786	32.04
	GJR-GARCH (1,1)	0.9881	57.90	0.9949	135.56	0.9756	28.06
	GARCH (1,1)	0.9676	21.04	0.9612	17.52	0.9762	28.78
S&P 500	EGARCH (1,1)	0.9474	12.83	0.9447	12.18	0.9398	11.16
	GJR-GARCH (1,1)	0.9627	18.21	0.9609	17.38	0.9774	30.32

Note: VP is the volatility persistence of the GARCH model and HL is the half-life perspective.

Moreover, Table 5.16 shows increase in the number of days for the volatility persistence and half-lives of IS2, IS3, MS and CS. It demonstrates that the shocks to volatility for these indices not only persist but also increased after the implementation of the financial reforms in Saudi Arabia. Therefore, these shocks can have a vital impact on Saudi stock index prices because changes in volatility affect the expected required rates of returns for relative intervals (Poterba & Summers 1984) in which case higher volatility, persistence and half-life imply higher returns and vice versa. This increase of the half-life and volatility persistence in the Saudi stock indices is inconstant with the efficiency of the Saudi stock market during the post-reform period (Goudarzi 2013). This could be due to increased speculation, increased uncertainty associated with the changes in regulation. These findings lead investors to enhance their forecasting of the Saudi stock market's performance by employing the risk premium factor.

5.8 Conclusion

This chapter examined the impact of relative stock market liberalisation on the Saudi stock market. To quantify this event, the study developed comparative estimates for returns volatility that had the goal of capturing the changes in five Saudi stock indices that are classified according to three Islamic standards (Ideal Ratings Saudi Islamic Index, S&P Saudi Arabia Shariah Index, MSCI Saudi Arabia Domestic Islamic Index, Tadawul All Share Index and S&P Saudi Arabia Domestic Islamic Index). To fulfil the study's objective, the comparison estimation employed returns and univariate volatility modelling techniques such as descriptive statistics and other stock market performance indicators (SR, TR, VaR and CVaR).

The study examined the daily returns of all the indices for stationarity by using the ADF, PP and KPSS tests. The ADF and PP tests had a 1% significance level, which indicates that all the variables were non-stationary. In addition, the KPSS findings matched the

ADF and PP tests, which indicates that all the series were stable in first differences for subsequent analysis stages.

According to the findings of the study, the average returns on the Saudi stock market have declined overall in the post reforms period. Further evidence may be found in the fact that the returns on Islamic stock indices dropped by less than those in the other indices categories: (IS1) 2.37 %, (IS2) 1.71 % and (IS3) 1.09 %. Meanwhile, mixed and non-Islamic indices had declines of −2.45% and −2.05%, respectively.

Furthermore, the analysis discovered that a decrease in the means of the Saudi indices returns is associated with a significant increase in the risk factor of the stock market (returns standard deviation) in the post reforms period. In other words, the risk involved with index returns rose during the time after the liberalising stock market reforms. Further, the standard deviation demonstrated that the Islamic stock indicators have distinctive characteristics that make them unique among other market indicators. However, according to the findings of the research, the growth in the Islamic indices returns standard deviation value was higher than the increase for the mixed and non-Islamic indices. Among the Islamic categories, the IS1, IS2 and IS3 standard deviations had increases of 19.45%, 12.44% and 38.13 %, respectively, during the years of the stock market reforms. Although the risk in the mixed stocks category grew by 13.95%, the risk in the non-Islamic stocks category increased by 14.57%.

CHAPTER 6: THE VOLATILITY SPILLOVER INVESTIGATION

6.1 Introduction

This chapter explores the return and volatility spillover between three categories of Saudi stock indices and three global markets (Brent, WTI, and S&P 500). Section 6.2 presents the first technique for estimating volatility spillover by including one global market in an ARMA equation of the Saudi stock index return, then modelling the volatility with a GARCH (1,1) framework. Section 6.3 presents the results of the cross-correlation function (CCF) approach for estimating the volatility spillover between the selected Saudi and global indices for the pre- and post-reform periods. Then, Section 6.4 introduces the results of a bivariate VAR-GARCH-BEKK estimation, which allows for a more comprehensive examination of the volatility spillover framework in Saudi Islamic and conventional stock indices and global markets.

Finally, the study extends the exploration of volatility spillover, a key component in the management of portfolios and risks. The estimations of optimal weights and hedge ratios, based on the bivariate VAR-GARCH-BEKK outcomes, will allow investors to quantify the degree of volatility spillover between Saudi stock indices and global markets, thereby enabling more informed investment decisions and mitigating portfolio risk.

6.2 ARMA-GARCH (1,1) Approach

This section examines the first spillover investigation technique between three Saudi stock index categories by the IFP and three global indices (Brent, WTI and S&P 500). Table 6.1 shows the results of the ARMA model with the GARCH (1,1) error term. Overall, the results of the ARMA-GARCH (1,1) estimation suggest that significant volatility spillover passes from the global markets to Saudi stock indices both pre- and post-reform, except for the IS3 during the pre-reform period. The findings of the ARMA-GARCH (1,1) estimation support the empirical findings of Grosvenor and Greenidge (2012) and Sun et al. (2023).

The results of the ARMA-GARCH (1,1) estimation for volatility spillover in Table 6.1 show that there is significant pre- and post-reform volatility spillover across the different markets. For instance, the coefficient of the independent variable for Brent in the pre-reform period is 0.0483, which is significant at the 1% confidence level. This suggests that the Brent index had a significant impact on the volatility of the Islamic stock index (IS1) in the pre-reform period. The same can be said for WTI and S&P 500, as their coefficients are significant at the 1% and 5% confidence levels, respectively. These results are in line with that reported by Albahooth and Kulendran (2020), who suggest the that the volatility of the oil market has a statistically significant impact on the volatility of the Saudi stock market in the long run.

In the post-reform period, the coefficients for all three global markets are significant at the 1% confidence level, indicating that the volatility spillover (transmission) among them was higher in the post-reform period. The other markets (Brent, WTI and S&P 500) yielded similar results, with significant coefficients at the 5% and 1% confidence levels in the pre- and post-reform periods, respectively.

The results of the ARMA-GARCH (1,1) estimation reveal an increase in volatility spillover between all the Saudi stock indices and global markets post-reform (see Table 6.1). For instance, the pre-reform coefficient of the independent variable for Brent was 0.0483, while in the post-reform period it was 0.0727, representing an increase of 50%. Similarly, the coefficient for WTI increased from 0.0362 to 0.0656, and the coefficient for S&P 500 increased from 0.1743 to 0.2851. These findings indicate that the reforms significantly impacted the volatility spillover from Brent, WTI and S&P 500 by increasing their size. This suggests that the Saudi stock market became stronger as a result of its integration with global events from mid-2015 to mid-2021.

The outcomes in Table 6.1 also show that the ARMA-GARCH (1,1) estimation indicates that the volatility spillover among the different markets, including the Saudi indices (IS1, IS2, IS3, MS and CS) and global markets (Brent, WTI and S&P 500), increased after the reforms were implemented. Specifically, the Islamic stock indices exhibited greater spillover growth with global markets than did MS and CS, suggesting market segmentation based on IFP. This result is in line with Shahzad et al. (2018), which suggests that Islamic assets exhibit a higher correlation with the global market compared to conventional assets. The liberalisation of the Saudi stock market may have increased the liquidity of the Islamic stock markets, allowing for greater integration with global markets. Additionally, the reforms may have reduced the complexity of the regulatory and legal environment, making it easier to invest in international markets. Finally, the reforms may have also led to improved transparency and disclosure requirements, which may have resulted in increased investor confidence and more capital flow between markets, especially in the Islamic stock indices.

Table 6.1: Results of ARMA-GARCH (1,1) Estimation for Volatility Spillover

Indicator	**Coefficient**		
	Independent Variables	**Pre-Reform Period**	**Post-Reform Period**
IS1	Brent	0.0483**	0.0727***
	WTI	0.0362***	0.0656***
	S&P 500	0.1743*	0.2851***
IS2	Brent	0.0463***	0.0702***
	WTI	0.0363**	0.0679***
	S&P 500	0.1827***	0.2163***
IS3	Brent	0.0038	0.0738***
	WTI	0.0044	0.0752***
	S&P 500	0.0048	0.2396***

MS	Brent	0.0520***	0.0667***
	WTI	0.0423***	0.0650***
	S&P 500	0.1867***	0.2381***
CS	Brent	0.0516***	0.0711***
	WTI	0.0427***	0.0691***
	S&P 500	0.1834***	0.2325***

Note: ***, ** and * refer to significance at the 1%, 5% and 10% confidence levels, respectively.

6.3 Cross-Correlation Function Approach

The results of the CCF test are summarised in the 45 combinations listed in Table 6.2 through Table 6.16. As explained by Cheung and Ng (1996), the CCF test consists of two stages. The first stage is to fit the univariate GARCH model and generate the standardised squared residuals. The second stage is to compare the obtained test statistics for the two indices to the critical value of N (0,1). If the value exceeds the critical value, the null hypothesis of no causality in the variance between the Saudi stock index (IS1, IS2, IS3, MS or CS) and one global market (Brent, WTI or S&P 500) is rejected. The lags and leads used in the CCF test refer to the time periods (days) during which the effects of volatility spillover are tested. The lag period is the amount of time that passes before the effects of volatility spillover are observed from the global market (Brent, WTI or S&P 500) to the Saudi stock index (IS1, IS2, IS3, MS or CS). The lead period is the amount of time that passes before the effects of volatility spillover are observed in the opposite direction (See Table 6.2 through Table 6.16).

The full period results in Table 6.2 through Table 6.16 indicate the presence of causalities in variance from all returns of the global indices (Brent, WTI and S&P 500) to the local Saudi stocks indices (IS1, IS2, IS3, MS and CS) at lag 0. This finding aligns with the prior study conducted by Finta et al. (2019). The variance of the Brent return is found to be significant, at the 5% level at minimum, in causing variance in the MS and CS returns. This causality in variance between Brent and MS was more than that of the Islamic indices, which presented lag 0 and lag 1 (see Table 6.2 through Table 6.6). According to Ahmed (2019), this could be attributed to the heavy dependence of the Saudi Arabian economy on oil, making it more susceptible to fluctuations in energy prices. The results in Table 6.7 to Table 6.16 for WTI and S&P 500 suggest the same, except that the null hypothesis of no causality in the variance between S&P 500 and IS1 and IS3 at lag 0 could not be rejected.

Table 6.2 reveals that the correlation between the variance of Brent and IS1 at lag 5 is the highest for both the full period (0.13) and the post-reform period (0.16), indicating that Brent is the leading market. Further, all the CCF estimations between Brent and the other Saudi stock indices point to the Saudi stock market as the leading one. Similarly, the CCF estimation between WTI and IS1 shows the highest value at a lag of 5 from WTI to IS1 in the full sample and during the post-reform period, implying that WTI is the leading market in these time periods. This is in contrast to the pre-reform period, where less correlation was observed between the variance of the two indices for the remaining markets.

The variance of the Brent return is found to increase the variance of all Saudi stocks index returns post-liberalisation compared to pre-reform. Table 6.7 through Table 6.11 indicate that the WTI variance causes variances in all Saudi stocks index returns at lag 0 and lag 1, with increased lag and lead values during the financial reform period. Table 6.12 through Table 6.16 demonstrate that the causality in variance between S&P 500 returns to IS1, IS2, IS3, MS and CS exists at lag 0, lag 1 and lag 10 in the post-reform period, except for the case of IS1 at lag 0. The same causality in variance is found to exist at lag 0, lag 1, lag 2, lag 3, lag 4 and lag 8 in the pre-reform period. The overall results of the

CCF test support the previous ARMA-GARCH estimation outcomes for volatility spillover between the local Saudi stock indices and global markets.

These CCF estimation research results may help investors and portfolio managers reduce their investment risks. The present results indicate that volatility spillover exists among the global markets, and Saudi stock indices are the main transmitters. Thus, investors can lower their risks by assessing the volatility of the leading markets and diversifying their investments globally, or vice versa, to account for volatility spillover.

Table 6.2: Causality in variance test results based on CCF testing for the full period (4/1/2010–29/6/2021, including pre- and post-reform)

	Full Period		Pre-Reform Period		Post-Reform Period	
Brent→IS1	***CCF statistic***		***CCF statistic***		***CCF statistic***	
Lag Order	Lag	Lead	Lag	Lead	Lag	Lead
0	0.0684	0.0684	0.0413	0.0413	0.0997	0.0997
1	0.0055	0.0512	0.0549	0.0761	-0.0071	0.0538
2	-0.0026	0.0102	0.0092	0.0793	-0.0040	-0.0080
3	0.0055	0.0134	-0.0154	0.0307	0.0138	0.0084
4	0.0570	0.0139	-0.0062	0.0784	0.0701	-0.0109
5	0.1304	0.0168	-0.0253	0.0153	0.1602	0.0206
6	-0.0051	-0.0025	-0.0173	-0.0118	-0.0041	-0.0015
7	0.0209	-0.0034	0.0025	0.0155	0.0323	-0.0083
8	0.0034	0.0166	0.0293	0.0194	-0.0042	0.0003
9	-0.0097	0.0063	0.0016	0.0515	-0.0209	-0.0057
10	-0.0046	-0.0030	-0.0293	-0.0365	0.0014	0.0454

Notes: The null hypothesis of causality in variance based on the CCF test is: H_0 = there is no causality in variance. The CCF statistic determines the time lag (lag order) between the two indices.

Table 6.3: Causality in variance test results based on CCF testing for the full period (4/1/2010–29/6/2021, including pre- and post-reform)

	Full Period		Pre-Reform Period		Post-Reform Period	
Brent→IS2	***CCF statistic***		***CCF statistic***		***CCF statistic***	
Lag Order	Lag	Lead	Lag	Lead	Lag	Lead
0	0.1928	0.1928	0.0368	0.0368	0.2612	0.2612
1	0.0113	0.0930	0.0522	0.0730	-0.0156	0.1076
2	0.0084	0.0222	0.0089	0.0758	0.0137	-0.0171
3	0.0182	0.0283	-0.0056	0.0277	0.0287	0.0264
4	0.0112	0.0183	0.0007	0.0719	0.0126	-0.0178
5	0.0230	0.0102	-0.0246	0.0166	0.0501	0.0055
6	-0.0096	0.0164	-0.0065	-0.0080	-0.0133	0.0262
7	0.0446	0.0044	0.0055	0.0166	0.0664	-0.0051
8	0.0277	0.0271	0.0321	0.0207	0.0195	0.0059
9	-0.0028	0.0277	0.0025	0.0644	-0.008	0.0053
10	0.0228	0.0070	-0.0341	-0.0277	0.0528	0.0781

Notes: The null hypothesis of causality in variance based on the CCF test is: H_0 = there is no causality in variance. The CCF statistic determines the time lag (lag order) between the two indices.

Table 6.4: Causality in variance test results based on CCF testing for the full period (4/1/2010–29/6/2021, including pre- and post-reform)

	Full Period		Pre-Reform Period		Post-Reform Period	
Brent→IS3	***CCF statistic***		***CCF statistic***		***CCF statistic***	
Lag Order	Lag	Lead	Lag	Lead	Lag	Lead
0	0.0555	0.0555	-0.0144	-0.0144	0.2576	0.2576
1	0.0043	0.0353	0.0128	0.012	-0.0163	0.1057
2	-0.0054	-0.0081	-0.0127	-0.006	0.0084	-0.0192
3	-0.0027	0.0076	-0.0163	-0.0043	0.0356	0.0321
4	-0.0039	-0.0073	-0.0126	-0.0032	0.01	-0.0223
5	-0.0020	-0.0091	-0.0185	-0.015	0.0429	0.0022
6	-0.0108	-0.0039	-0.0121	-0.0171	-0.0102	0.0247
7	0.0123	-0.0055	-0.0033	-0.0053	0.0651	-0.0065
8	0.0072	0.0020	0.0004	-0.0057	0.0191	0.0081
9	-0.0073	0.0006	-0.0094	0.0011	-0.0095	0.0094
10	0.0341	-0.0036	0.0216	-0.0176	0.0492	0.0728

Notes: The null hypothesis of causality in variance based on the CCF test is: H_0 = there is no causality in variance. The CCF statistic determines the time lag (lag order) between the two indices.

Table 6.5: Causality in variance test results based on CCF testing for the full period (4/1/2010–29/6/2021, including pre- and post-reform)

	Full Period		Pre-Reform Period		Post-Reform Period	
Brent→MS	***CCF statistic***		***CCF statistic***		***CCF statistic***	
Lag Order	Lag	Lead	Lag	Lead	Lag	Lead
0	0.2173	0.2173	0.0487	0.0487	0.2835	0.2835
1	0.0087	0.0943	0.0498	0.0679	-0.0168	0.1123
2	0.0099	0.0305	0.013	0.0937	0.0164	-0.0143
3	0.0141	0.0288	-0.0099	0.0318	0.0249	0.0245
4	0.0058	0.0216	-0.0016	0.0855	0.0049	-0.0180
5	0.0165	0.0091	-0.0247	0.0144	0.0388	0.0063
6	-0.0117	0.0190	-0.0122	-0.0083	-0.0135	0.0295
7	0.0482	0.0054	0.0030	0.0132	0.0726	-0.0017
8	0.0262	0.0274	0.0345	0.0300	0.0172	0.0042
9	0.0001	0.0260	0.0122	0.0639	-0.0077	0.0041
10	0.0195	0.0088	-0.0275	-0.0361	0.0434	0.0768

Notes: The null hypothesis of causality in variance based on the CCF test is: H_0 = there is no causality in variance. The CCF statistic determines the time lag (lag order) between the two indices.

Table 6.6: Causality in variance test results based on CCF testing for the full period (4/1/2010–29/6/2021, including pre- and post-reform)

Full Period			Pre-Reform Period		Post-Reform Period	
Brent→CS	***CCF statistic***		***CCF statistic***		***CCF statistic***	
Lag Order	Lag	Lead	Lag	Lead	Lag	Lead
0	0.2056	0.2056	0.0452	0.0452	0.2717	0.2717
1	0.0091	0.0915	0.0499	0.0684	-0.0173	0.1074
2	0.0086	0.0306	0.0112	0.0929	0.0154	-0.0161
3	0.0145	0.0301	-0.0084	0.0314	0.0247	0.0264
4	0.0077	0.0216	0.0008	0.0825	0.0066	-0.0179
5	0.0178	0.0096	-0.0249	0.0164	0.0419	0.0052
6	-0.0108	0.0193	-0.0106	-0.0064	-0.0134	0.0297
7	0.0465	0.0051	0.0049	0.0128	0.0693	-0.0022
8	0.0276	0.0292	0.0359	0.0290	0.0179	0.0056
9	-0.0002	0.0283	0.0109	0.0688	-0.0078	0.0042
10	0.0209	0.0069	-0.0280	-0.0348	0.0475	0.0784

Notes: The null hypothesis of causality in variance based on the CCF test is: H_0 = there is no causality in variance. The CCF statistic determines the time lag (lag order) between the two indices.

Table 6.7: Causality in variance test results based on CCF testing for the full period (4/1/2010–29/6/2021, including pre- and post-reform)

Full Period			Pre-Reform Period		Post-Reform Period	
WTI→IS1	***CCF statistic***		***CCF statistic***		***CCF statistic***	
Lag Order	Lag	Lead	Lag	Lead	Lag	Lead
0	0.0876	0.0876	0.0589	0.0589	0.1247	0.1247
1	-0.0051	0.0320	0.0631	0.0026	-0.0166	0.0513
2	-0.0033	0.0098	0.0263	0.1109	-0.0112	-0.0118
3	0.0134	0.0168	-0.0133	0.0725	0.0253	0.0072
4	0.0576	-0.0062	-0.0108	0.0086	0.0741	-0.0114
5	0.1615	0.0027	-0.0251	-0.0059	0.1897	0.0044
6	-0.0019	-0.011	0.0018	-0.0219	-0.0028	-0.0084
7	0.0022	-0.0087	0.0034	0.0135	0.0035	-0.0134
8	0.0112	-0.0001	0.0570	0.0156	-0.0029	-0.0057
9	-0.0215	0.0068	-0.0238	0.0113	-0.0238	0.0155
10	0.0015	0.0054	-0.0076	-0.0130	0.0044	0.0142

Notes: The null hypothesis of causality in variance based on the CCF test is: H_0 = there is no causality in variance. The CCF statistic determines the time lag (lag order) between the two indices.

Table 6.8: Causality in variance test results based on CCF testing for the full period (4/1/2010–29/6/2021, including pre- and post-reform)

	Full Period		Pre-Reform Period		Post-Reform Period	
WTI→IS2	***CCF statistic***		***CCF statistic***		***CCF statistic***	
Lag Order	Lag	Lead	Lag	Lead	Lag	Lead
0	0.2430	0.2430	0.0545	0.0545	0.3253	0.3253
1	0.0000	0.0777	0.0544	0.0016	-0.0237	0.1205
2	0.0020	0.0361	0.0221	0.1187	-0.0042	-0.0099
3	0.0244	0.0413	-0.0079	0.0711	0.0384	0.0254
4	0.0054	-0.0077	-0.0114	0.0107	0.0133	-0.0162
5	0.0365	-0.0061	-0.0244	-0.0071	0.0655	-0.0071
6	-0.0031	-0.0053	0.0151	-0.0233	-0.0130	0.0045
7	0.0117	-0.0037	0.0093	0.0200	0.0129	-0.0157
8	0.0341	0.0051	0.0623	0.0176	0.0168	0.0010
9	-0.0164	0.0142	-0.0254	0.0179	-0.0114	0.0203
10	0.0395	0.0252	-0.0128	-0.0056	0.0651	0.0434

Notes: The null hypothesis of causality in variance based on the CCF test is: H_0 = there is no causality in variance. The CCF statistic determines the time lag (lag order) between the two indices.

Table 6.9: Causality in variance test results based on CCF testing for the full period (4/1/2010–29/6/2021, including pre- and post-reform)

	Full Period		Pre-Reform Period		Post-Reform Period	
WTI→IS3	***CCF statistic***		***CCF statistic***		***CCF statistic***	
Lag Order	Lag	Lead	Lag	Lead	Lag	Lead
0	0.0808	0.0808	0.0000	0.000	0.3231	0.3231
1	0.0059	0.0303	0.0240	0.000	-0.0248	0.1199
2	-0.0031	-0.0048	-0.0050	0.002	-0.0070	-0.0116
3	0.0016	0.0029	-0.015	-0.011	0.0458	0.0300
4	-0.0059	-0.0136	-0.015	-0.014	0.0090	-0.0226
5	0.0042	-0.0059	-0.017	-0.009	0.0570	-0.0069
6	-0.0108	-0.0034	-0.013	-0.010	-0.0093	0.0033
7	-0.0013	-0.0104	-0.010	-0.009	0.0117	-0.0157
8	0.0042	-0.0052	-0.001	-0.011	0.0163	0.0011
9	-0.0115	-0.0020	-0.016	-0.001	-0.0127	0.0193
10	0.0481	0.0022	0.039	-0.016	0.0639	0.0408

Notes: The null hypothesis of causality in variance based on the CCF test is: H_0 = there is no causality in variance. The CCF statistic determines the time lag (lag order) between the two indices.

Table 6.10: Causality in variance test results based on CCF testing for the full period (4/1/2010–29/6/2021, including pre- and post-reform)

	Full Period		Pre-Reform Period		Post-Reform Period	
WTI→MS	***CCF statistic***		***CCF statistic***		***CCF statistic***	
Lag Order	Lag	Lead	Lag	Lead	Lag	Lead
0	0.2698	0.2698	0.0636	0.0636	0.3505	0.3505
1	-0.0004	0.0836	0.0556	0.0019	-0.0242	0.1266
2	0.0050	0.0384	0.0294	0.1216	-0.0015	-0.0079
3	0.0256	0.0401	-0.0038	0.0722	0.0372	0.0228
4	0.0005	-0.0081	-0.0102	0.0123	0.0052	-0.0168
5	0.0313	-0.0053	-0.0226	-0.0055	0.0558	-0.0062
6	-0.0044	-0.0029	0.0108	-0.0215	-0.0121	0.0063
7	0.0106	-0.0029	0.0047	0.0128	0.0140	-0.0110
8	0.0316	0.0073	0.0628	0.0302	0.0160	-0.0004
9	-0.0162	0.0102	-0.0222	0.0133	-0.0130	0.0142
10	0.0342	0.0258	-0.0061	-0.0095	0.0542	0.0450

Notes: The null hypothesis of causality in variance based on the CCF test is: H_0 = there is no causality in variance. The CCF statistic determines the time lag (lag order) between the two indices.

Table 6.11: Causality in variance test results based on CCF testing for the full period (4/1/2010–29/6/2021, including pre- and post-reform)

	Full Period		Pre-Reform Period		Post-Reform Period	
WTI→CS	***CCF statistic***		***CCF statistic***		***CCF statistic***	
Lag Order	Lag	Lead	Lag	Lead	Lag	Lead
0	0.2562	0.2562	0.0593	0.0593	0.3375	0.3375
1	-0.0009	0.0789	0.0539	0.0018	-0.0252	0.1209
2	0.0054	0.0389	0.0293	0.1228	-0.0011	-0.0102
3	0.0256	0.0414	-0.0018	0.0712	0.0362	0.0243
4	0.0023	-0.0067	-0.0079	0.0154	0.0067	-0.0165
5	0.0326	-0.0058	-0.0230	-0.0070	0.0590	-0.0066
6	-0.0032	-0.0025	0.0136	-0.0211	-0.0122	0.0073
7	0.0113	-0.0028	0.0074	0.0136	0.0136	-0.0118
8	0.034	0.0072	0.0664	0.0287	0.0164	-0.0001
9	-0.0158	0.0115	-0.0226	0.0133	-0.0121	0.0168
10	0.0364	0.0249	-0.0061	-0.0085	0.0590	0.0442

Notes: The null hypothesis of causality in variance based on the CCF test is: H_0 = there is no causality in variance. The CCF statistic determines the time lag (lag order) between the two indices.

Table 6.12: Causality in variance test results based on CCF testing for the full period (4/1/2010–29/6/2021, including pre- and post-reform)

	Full Period		Pre-Reform Period		Post-Reform Period	
S&P 500 →IS1	***CCF statistic***		***CCF statistic***		***CCF statistic***	
Lag Order	Lag	Lead	Lag	Lead	Lag	Lead
0	0.0423	0.0423	0.0978	0.0978	0.0382	0.0382
1	0.0057	0.0519	0.0374	0.0713	-0.0035	0.0547
2	0.0046	0.0411	-0.0007	0.1254	0.0044	0.0320
3	-0.0069	0.0083	-0.0094	0.0600	-0.0071	-0.0022
4	-0.0115	0.0410	-0.0366	0.0962	-0.0054	0.0224
5	0.0128	0.0732	-0.0364	-0.0011	0.0210	0.0859
6	0.0013	0.0159	0.0065	-0.0109	0.0022	0.0228
7	-0.0125	-0.0076	0.0005	-0.0209	-0.0191	-0.0040
8	0.0191	0.0408	0.0388	0.0676	0.0127	0.0348
9	-0.0089	0.0247	-0.0325	0.0026	-0.0038	0.0287
10	-0.0012	0.0159	-0.0404	-0.0331	0.0058	0.0387

Notes: The null hypothesis of causality in variance based on the CCF test is: H_0 = there is no causality in variance. The CCF statistic determines the time lag (lag order) between the two indices.

Table 6.13: Causality in variance test results based on CCF testing for the full period (4/1/2010–29/6/2021, including pre- and post-reform)

	Full Period		Pre-Reform Period		Post-Reform Period	
S&P 500 →IS2	***CCF statistic***		***CCF statistic***		***CCF statistic***	
Lag Order	Lag	Lead	Lag	Lead	Lag	Lead
0	0.1092	0.1092	0.0905	0.0905	0.1204	0.1204
1	0.0172	0.0873	0.0505	0.0614	-0.0027	0.0965
2	0.0099	0.0604	-0.0023	0.1353	0.0150	0.0240
3	0.0108	0.0237	-0.0018	0.0503	0.0146	0.0097
4	-0.0088	0.0357	-0.0270	0.0951	-0.0009	-0.0012
5	0.0034	0.0183	-0.0385	-0.0018	0.0226	0.0268
6	-0.0002	0.0058	0.0194	-0.0045	-0.0115	0.0150
7	-0.0086	0.0059	0.0020	-0.0074	-0.0183	0.0081
8	0.0228	0.0292	0.0513	0.0615	0.0078	0.0093
9	-0.0112	0.0092	-0.0296	0.0063	0.0025	0.0063
10	-0.0071	0.0784	-0.0322	-0.0305	0.0072	0.1323

Notes: The null hypothesis of causality in variance based on the CCF test is: H_0 = there is no causality in variance. The CCF statistic determines the time lag (lag order) between the two indices.

Table 6.14: Causality in variance test results based on CCF testing for the full period (4/1/2010–29/6/2021, including pre- and post-reform)

	Full Period		Pre-Reform Period		Post-Reform Period	
S&P 500 →IS3	***CCF statistic***		***CCF statistic***		***CCF statistic***	
Lag Order	Lag	Lead	Lag	Lead	Lag	Lead
0	0.0256	0.0256	-0.0115	-0.0115	0.1158	0.1158
1	-0.0057	0.0232	-0.0133	-0.0041	-0.0015	0.0984
2	-0.0029	0.0206	-0.0124	0.0224	0.0105	0.0302
3	0.0950	0.0048	0.1486	0.0047	0.0113	0.0108
4	-0.0133	-0.0077	-0.0217	-0.0116	0.0025	-0.0024
5	0.0020	-0.0099	-0.0129	-0.0246	0.0237	0.0175
6	-0.0057	0.0000	-0.0045	-0.0045	-0.0090	0.0137
7	-0.0084	0.0160	-0.0075	0.0189	-0.0197	0.0088
8	0.0303	-0.0037	0.0499	-0.0114	0.0112	0.0088
9	-0.0086	-0.0049	-0.0154	-0.0137	0.0015	0.0084
10	-0.0082	0.0195	-0.0166	-0.0212	0.0075	0.1327

Notes: The null hypothesis of causality in variance based on the CCF test is: H_0 = there is no causality in variance. The CCF statistic determines the time lag (lag order) between the two indices.

Table 6.15: Causality in variance test results based on CCF testing for the full period (4/1/2010–29/6/2021, including pre- and post-reform)

	Full Period		Pre-Reform Period		Post-Reform Period	
S&P 500 →MS	***CCF statistic***		***CCF statistic***		***CCF statistic***	
Lag Order	Lag	Lead	Lag	Lead	Lag	Lead
0	0.1142	0.1142	0.1141	0.1141	0.1155	0.1155
1	0.0155	0.0844	0.0458	0.0611	-0.0003	0.0919
2	0.0104	0.0635	0.0002	0.1531	0.0148	0.0211
3	0.0141	0.0256	0.0045	0.0529	0.0161	0.0126
4	-0.0035	0.0418	-0.0244	0.1167	0.0054	-0.0023
5	0.0072	0.0163	-0.0346	-0.0058	0.0244	0.0257
6	-0.0051	0.0034	0.0008	-0.0085	-0.0089	0.0138
7	-0.0083	0.0072	-0.0027	-0.0194	-0.0143	0.0149
8	0.0145	0.0277	0.0417	0.0718	0.0004	0.0022
9	-0.0159	0.0147	-0.0344	0.0151	-0.0043	0.0100
10	-0.0108	0.0904	-0.0350	-0.0280	0.0014	0.1446

Notes: The null hypothesis of causality in variance based on the CCF test is: H_0 = there is no causality in variance. The CCF statistic determines the time lag (lag order) between the two indices.

Table 6.16: Causality in variance test results based on CCF testing for the full period (4/1/2010–29/6/2021, including pre- and post-reform)

	Full Period		Pre-Reform Period		Post-Reform Period	
S&P 500 →CS	***CCF statistic***		***CCF statistic***		***CCF statistic***	
Lag Order	Lag	Lead	Lag	Lead	Lag	Lead
0	0.1121	0.1121	0.1072	0.1072	0.1166	0.1166
1	0.0164	0.0866	0.0469	0.0593	-0.0004	0.0973
2	0.0078	0.0641	-0.0004	0.1527	0.0116	0.0199
3	0.0130	0.0271	0.0050	0.0543	0.0143	0.0134
4	-0.0029	0.0429	-0.0212	0.1149	0.0049	-0.0016
5	0.0070	0.0156	-0.0322	-0.0060	0.0241	0.0252
6	-0.0051	0.0055	0.0019	-0.0045	-0.0100	0.0153
7	-0.0081	0.0041	-0.0002	-0.0194	-0.0158	0.0107
8	0.0180	0.0293	0.0428	0.0693	0.0049	0.0048
9	-0.0143	0.0150	-0.0349	0.0162	-0.0006	0.0099
10	-0.0086	0.0851	-0.0326	-0.0279	0.0045	0.1392

Notes: The null hypothesis of causality in variance based on the CCF test is: H_0 = there is no causality in variance. The CCF statistic determines the time lag (lag order) between the two indices.

6.4 Bivariate GARCH Approach

This section presents the findings of the third technique for investigating volatility spillover between the five Saudi stock indices (constructed based on IFP) and the three global markets (Brent, WTI and S&P 500). The analysis is conducted using a bivariate VAR-GARCH-BEKK model. The aim of this investigation is to examine the effects of the liberalisation reforms and COVID-19 on the volatility spillover between Saudi Islamic and conventional stock indices and three global markets, namely Brent, WTI and S&P 500. The results of the VAR-GARCH-BEKK estimations are discussed in the following sections in terms of the existence, direction and magnitude of the observed volatility spillover.

6.4.1 Bivariate VAR GARCH BEKK (1,1) Estimations Results

The volatility and cross-volatility spillover among Saudi stock indices and the selected global markets are captured using a conditional variance–covariance equation. To estimate the outcomes of time-varying variance–covariance, the study applies the bivariate VAR-GARCH-BEKK approach. This also helps to quantify the relationships between returns in the Saudi stock indices, created by IFP, the oil market (Brent/WTI) and the US equity market (S&P 500). Returns data from five Saudi stock market indices, Brent, WTI and the S&P 500 index are used to estimate the GARCH BEKK model.

According to Doan (2013), the A and B diagonals coefficients in the matrices indicate the influence of previous information shocks and market volatility on their own current volatility, respectively. The a_{11} coefficient quantifies the effect of previous spillover shocks on Saudi stock indices' conditional variance (ARCH effect), while the b_{11} coefficient quantifies the effect of past volatility spillover on the conditional variance

(GARCH effect) of the Saudi index. Then, a_{22} and b_{22} capture the impact of previous information shocks and quantify the volatility spillover from the previous value for the conditional variance of the global index on its own current value.

For the off-diagonal A and B matrices parameters, the coefficients indicate the influence of previous information shocks and market volatility cross-markets. Specifically, a_{12} represents the effect of previous information shocks from the Saudi stock indices (ARCH effect) on the global indices. Meanwhile, b_{12} reports the spillover of volatility (GARCH effect) from the Saudi market to the global market. In the other directional pattern, a_{21} shows the influence of previous information shocks from the global index on the Saudi market. The coefficient b_{21} captures the spillover of volatility from the global market to the Saudi indices.

6.4.1.1 Full Study Period (January 2010 to June 2021)

Table 6.17 and Table 6.18 illustrate the significant return spillover to the three Saudi stock index categories (Islamic, mixed and non-Islamic) from the oil market (Brent and WTI) and the S&P 500 index. This data is based on the VAR-GARCH-BEKK model from the full sample period. The overall results suggest that the Saudi stock indices show a positive reaction to changes in the oil market and US stock market, which implies that these markets have a profound influence on the Saudi market. Additionally, the data demonstrate that the Islamic and mixed stock indices have a stronger correlation to the oil market and US stock market compared to the non-Islamic index. This highlights the importance of Islamic financial principles when investing in the Saudi stock market.

Shocks and Spillover Between the Saudi Market and Oil Market

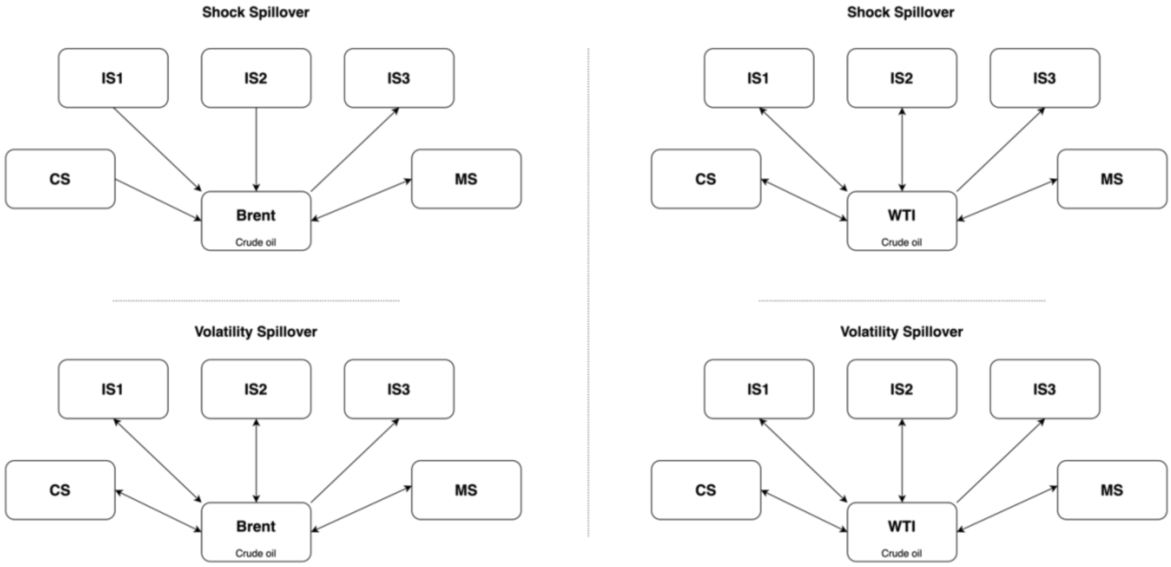
According to the bivariate VAR-GARCH-BEKK estimation illustrated in Table 6.17, a_{11} shows significant evidence of the previous information shock on the Saudi stock indices' own current value at a 1% confidence level. Similarly, a_{22} reports a 1% significant level of influence of its own past information shock (ARCH effect) on the global oil market (Brent and WTI) and equity market (S&P 500). The coefficient a_{12} reveals evidence at 1% significance of negative cross-market information shocks from the Saudi indices to Brent and WTI, with the exception of the IS3. The highest shocks recorded among the Saudi indices are from the CS index (-0.2042), IS2 index (-0.2025), MS (-0.1954) and IS1 (-0.1826) to the Brent index. In the reverse direction, a_{21} shows no statistical evidence of any cross-market shocks from the Brent crude oil index to Saudi stocks, other than positive shocks (0.0952) of 5% significance in the MS index. The other oil market indicator shows strong evidence of positive information shocks from WTI to all Saudi indices at a 1% confidence level.

The findings of this study are in line with the results of Basher and Sadorsky (2006), Hammoudeh and Choi (2006), Jouini (2013), Gomes and Chaibi (2014), and Jouini and Harrathi (2014), who found that increased oil prices have a positive influence on stock returns in emerging markets. This suggests that oil price increases can result in greater returns for investors in the Saudi stock indices. Conversely, Arouri et al. (2011) report that the oil market has a strong influence on stock market returns in most GCC countries, while the opposite is not statistically significant. The present study asserts that influence runs both ways. The oil markets and Saudi stock indices influence each other in both directions, suggesting a strong relationship between the oil and stock markets in Saudi Arabia.

The results also show that the IS1 has a greater coefficient value (0.1424) than the non-Islamic stock indices. The two observed non-Islamic stock indices, MS and CS, have coefficients values of 0.1153 and 0.0789, respectively. This indicates that the IS1 index correlates more with the oil market than do the non-Islamic indices.

Furthermore, volatility spillover coefficients from b_{11} report a 1% significant level, which suggests influence from prior Saudi volatility on its current value (see Table 36). As for the Saudi stocks indices from the Brent and WTI bivariate BEKK estimations, the Saudi indices are observed to have their own influence patterns with slightly higher values in the WTI estimation. Additionally, b_{22} presents positive evidence at 1% significance that Brent's and WTI's own pasts affect their current volatility. Regarding cross-market effects, volatility spillover from the Saudi indices to Brent crude oil (b_{12}) is shown in Table 36. IS1 records high volatility spillover to Brent with 0.2459 at a 10% significance level. Meanwhile, the IS2, MS and CS indices exhibit positive volatility spillover to the Brent index with a 1% significance level. IS3 shows no evidence of volatility spillover to Brent or WTI. In addition to Brent, b_{12} indicates evidence at 1% significance of positive volatility spillover from the IS1, IS2, MS and CS indices to WTI. However, the oil market, whether Brent or WTI, tends to exhibit overall negative volatility spillover to the Saudi stock markets at 1% significance. Furthermore, according to Table 6.17, the volatility spillover from both oil markets is lower than the volatility spilled in the other direction.

Figure 6.1: Dynamic shocks and volatility spillover between Saudi stock indices and the global oil market for the full period (January 2010–June 2021).



Note: → and ← indicate one way shock or volatility spillover; ↔indicates bidirectional shock or volatility spillover between the Saudi and global oil markets.

Table 6.17: Results of bivariate VAR-GARCH-BEKK (1,1) estimation for daily shocks and volatility spillover between the Saudi market and oil market

	Full Period *(from 04/01/2010 to 29/06/2021)*									
	Brent					**WTI**				
	IS1	**IS2**	**IS3**	**MS**	**CS**	**IS1**	**IS2**	**IS3**	**MS**	**CS**
a_{11}	0.2280***	0.2923***	0.2883***	0.2949***	0.2883***	0.2312***	0.2827***	0.2871***	0.2525***	0.2799***
a_{12}	-0.1826**	-0.2025***	0.1048	-0.1954***	-0.2042***	-0.1156***	-0.1250***	-0.0758	-0.2011***	-0.1187***
a_{21}	0.1437	0.0714	-0.0117*	0.0952**	0.0750	0.1114***	0.0778**	0.0125**	0.1153***	0.0789**
a_{22}	0.2566	0.2479***	0.3184***	0.2182***	0.2450***	0.3334***	0.2494***	0.2994***	0.2519***	0.2469***
b_{11}	0.9289***	0.9263***	0.9665***	0.9142***	0.9287***	0.9574***	0.9318***	0.9678***	0.9469***	0.9348***
b_{12}	0.2459*	0.1324***	-0.0188	0.1476***	0.1361***	0.1530***	0.0849***	0.0213	0.2996***	0.0860***
b_{21}	-0.0624***	-0.0144**	0.0056**	-0.0193***	-0.0158**	-0.0606***	-0.0159**	-0.0060**	-0.0726***	-0.0168**
b_{22}	0.9241***	0.9490***	0.9436***	0.9544***	0.9483***	0.9099***	0.9549***	0.9484***	0.9046***	0.9548***
	Diagnostics Tests									
Log L.	-10423	-10364	-9611	-10370	-10401	-10115	-10084	-9330	-10113	-10124
LBQ^2 (20)	32.7766**	221.5199***	3.6122	245.3383***	237.0251***	19.8413	213.4760***	3.9561	216.1112***	219.3205***

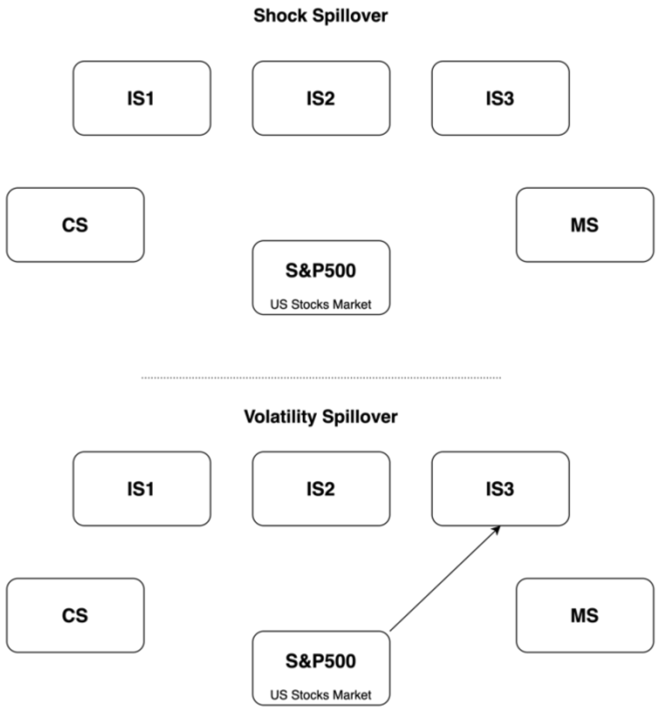
Notes: A and B capture shock and volatility effects, respectively. The a11 coefficient reflects the effect of previous shocks from the Saudi stock index on its own current shock; a12 indicates the ARCH effect of shocks from the local Saudi index to the global market index; a21 shows that cross-market shocks from the global index to the Saudi stock indices also have an ARCH effect; a22 captures the impact of previous shocks from each global market on its own current shock. Also, b11 explores the effect of past volatility on the current conditional variance of the Saudi stock indices; b12 captures the volatility spillover from the Saudi stock indices to the global market; b21measures the volatility spillover from the global market to the Saudi stock indices; b22 captures the volatility spillover from each global indices' conditional variance to its own. Further, the diagnostics tests section presents the LogL (log likelihood) for the bivariate BEKK estimation, where LBQ2 (20) is the Ljung-BoxQ statistic up to 20 lags. Significance levels of ***, ** and * indicate that the null hypothesis is rejected at 1%, 5%, and 10%, respectively.

The findings from the bivariate VAR-GARCH-BEKK estimation, which compared the five indices in the Saudi stock market (IS1, IS2, IS3, MS and CS) to the US stock market (S&P 500), indicate significant shock and volatility spillover between the two markets (see Table 6.18). Specifically, the information shocks and volatility spillover from the S&P 500 index to the Saudi stock market indices were found to be statistically significant. This implies that the US stock market is an important source of information shocks and volatility spillover to the Saudi stock market. The findings also indicate that the Saudi stock market indices are significantly affected by shocks in the US stock market. This means that investors in the Saudi stock market should pay close attention to the US stock market to better understand the dynamics of their investment.

The coefficients from the a_{11} report indicate that the Saudi stock indices are significantly influenced by their own previous volatility, with a significance level of 1%. The ranking of the Saudi stocks indices from their own shocks is IS1 (0.3714), MS (0.3084), IS2 (0.3052), CS (0.2999) and IS3 (0.2962). Similarly, the coefficients from a_{22} suggest that the information shock (ARCH effect) of the S&P 500 index is also significantly influenced by its own previous shocks, with a significance level of 1%. This indicates that the information shocks between the Saudi market and oil indices are significantly influential on their current values.

The findings shown in Table 6.18 are consistent with those reported in Awartani et al.'s (2013) study on the volatility spillover between the US and Saudi stock markets. The a_{12} and a_{21} coefficients exhibit insignificant statistical evidence, indicating no shock effect in either direction between the Saudi stock indices and S&P 500. Likewise, the b_{12} and b_{21} coefficients of volatility spillover between the two markets fail to show any significant evidence in either direction. This suggests a lack of information shock between the two markets.

Figure 6.2: Dynamic shocks and volatility spillover between Saudi stocks indices and the US stock market for the full period (January 2010–June 2021).



Note: → and ← indicate one way shock or volatility spillover; ↔indicates bidirectional shock or volatility spillover between the Saudi and US stock markets.

Table 6.18: Results of bivariate VAR-GARCH BEKK (1,1) estimation for daily shock and volatility spillover between the Saudi and US stock markets.

	Full Period *(04/01/2010–29/06/2021)*				
	S&P 500				
	IS1	**IS2**	**IS3**	**MS**	**CS**
a_{11}	0.3714***	0.3052***	0.2962***	0.3084***	0.2999***
a_{12}	0.0252	-0.0071	0.0020	-0.0071	-0.0097
a_{21}	-0.1037	0.0155	0.0027	0.0319	0.0306
a_{22}	0.4108***	0.4426***	0.4284***	0.4405***	0.4431***
b_{11}	0.8702***	0.9372***	0.9649***	0.9368***	0.9405***
b_{12}	-0.0077	0.0073	0.0068	0.0062	0.0077
b_{21}	0.0485	0.0069	-0.0009*	-0.0021	-0.0018
b_{22}	0.8941***	0.8802***	0.8845***	0.8818***	0.8804***
	Diagnostics Tests				
Log L.	-7810	-7742	-7019	-7753	-7780
LBQ^2 (20)	21.2361	204.9962***	3.9525	225.2078***	236.9161***

Notes: A and B capture the shock and volatility effects, respectively. The a_{11} coefficient reflects the effect of previous shocks from the Saudi stock index on its own current shock; a_{12} indicates the ARCH effect of shocks from the local Saudi index to the global market index; a_{21} shows that cross-market shocks from the global index to the Saudi stock indices also have an ARCH effect; and a_{22} captures the impact of previous shocks from each global market on its own current shock. Further, b_{11} explores the effect of past volatility on the current conditional variance of the Saudi stock indices; b_{12} captures the volatility spillover from the Saudi stock indices to the global market; b_{21}measures the volatility spillover from the global market to the Saudi stock indices; and b_{22} captures the volatility spillover from each global index's conditional variance to its own. The diagnostics tests section presents the LogL (log likelihood) for the bivariate BEKK estimation, where LBQ^2 (20) is the Ljung-BoxQ statistic up to 20 lags. Significance levels of ***, ** and * indicate that the null hypothesis is rejected at 1%, 5% and 10%, respectively.

6.4.1.2 Pre-Reform Period (January 2010–May 2015)

As in the previous section, Table 6.19 through Table 6.21 show the results of a bivariate VAR-GARCH-BEKK (1,1) estimation for the pre-reform period between Saudi stock indices and S&P 500, Brent and WTI. It presents the estimated coefficients for the shock and volatility effects (A and B), as well as diagnostic tests for each estimation.

The a_{11} coefficient reflects the effect of previous shocks from the Saudi stock index's own conditional variance, while a_{12} captures the overall shock (ARCH effect) from the local Saudi index on the global market index. Then, a_{21} reveals that cross-market shocks from the global markets (Brent, WTI and S&P 500) have an ARCH effect on the local Saudi market, and a_{22} captures the impact of past shocks from the global market on its own shock.

The b_{11} coefficient explores the effect of past volatility on its own current volatility, while b_{12} captures the volatility spillover from local Saudi market on the global market index. Then, b_{21} measures the volatility spillover from the S&P 500 index to the Saudi stock indices, and b_{22} captures the volatility spillover from S&P 500's past conditional variance (volatility) to its current value.

Table 6.19 through Table 6.21 present the diagnostic tests conducted, including the LogL (log likelihood) for the bivariate BEKK estimation used to evaluate overall model fit. The LBQ2 (20) refers to the Ljung-BoxQ statistics up to 20 lags. Meanwhile, ***, ** and * indicate the null hypothesis is rejected at the significance levels of 1%, 5% and 10%, respectively.

Shocks and Spillover Between Saudi Stock Indices and S&P 500

The outcomes shown in Table 6.19 illustrate the estimated coefficients from the pre-reform period. The pre-reform results suggest the significant effect of both own past shock (ARCH) and own past volatility (GARCH) for both the Saudi stock indices (IS1, IS2, IS3, MS and CS) and S&P 500. However, there is no significant evidence of shock and volatility spillover between the Saudi stock indices and S&P 500 during this period. Table 6.19 also reveals that the cross-market volatility linkages from the MS and CS markets to S&P 500 are higher than those of the Islamic stock indices (IS1, IS2 and IS3). However, the differences are not statistically significant. Furthermore, the findings illustrate that the MS and CS markets are more volatile and prone to shocks from S&P 500 compared to the Islamic stock indices.

Table 6.19: Results of the bivariate VAR-GARCH BEKK (1,1) estimation for the pre-reform period between the Saudi stock indices and S&P 500.

	Pre-Reform Period *(04/01/2010–15/05/2015)*				
	S&P 500				
	IS1	**IS2**	**IS3**	**MS**	**CS**
a_{11}	0.3588***	0.3509***	0.3542***	0.3610***	0.3639***
a_{12}	0.0493	0.0760	0.0011	0.0716	0.0667
a_{21}	0.0105	0.0029	0.0186	0.0003	-0.0013
a_{22}	0.2833***	0.2910***	0.2881***	0.2851***	0.2748***
b_{11}	0.9107***	0.9129***	0.9121***	0.9096***	0.9082***
b_{12}	-0.0134	-0.0233	-0.0004	-0.0202	-0.0191
b_{21}	0.0028	0.0054	0.0023	0.0056	0.0069
b_{22}	0.9430***	0.9423***	0.9653***	0.9415***	0.9460***
	Diagnostic Tests				
Log L.	-3347	-3505	-2647	-3496	-3509
LBQ^2 (20)	150.5423 (4.9488e-22)	185.3721 (8.5928e-29)	0.7324 (1.0000)	213.8491 (2.0089e-34)	208.0555 (2.8496e-33)

Notes: A and B capture the shock and volatility effects, respectively. The a_{11} coefficient reflects the effect of previous shocks from the Saudi stock index on its own current shock; a_{12} indicates the ARCH effect of shocks from the local Saudi index to the global market index; a_{21} shows that cross-market shocks from the global index to the Saudi stock indices also have an ARCH effect; and a_{22} captures the impact of previous shocks from each global market on its own current shock. Then, b_{11} explores the effect of past volatility on the current conditional variance of the Saudi stock indices; b_{12} captures the volatility spillover from the Saudi stock indices to the global market; b_{21}measures the volatility spillover from the global market to the Saudi stock indices; and b_{22} captures the volatility spillover from each global index's conditional variance to its own. The diagnostic tests present the LogL (log likelihood) for the bivariate BEKK estimation, where LBQ^2 (20) is the Ljung-BoxQ statistic up to 20 lags. Significance levels of ***, ** and * refers to the null hypothesis is rejected at 1%, 5% and 10%, respectively.

In terms of the spillover of shock and volatility between the oil markets and Saudi stock indices, the results of the bivariate VAR-GARCH BEKK (1,1) estimation for the pre-reform period indicate significant spillover effects between the Saudi stock indices and Brent (see Table 6.20). Specifically, the results show that a significant ARCH effect from the local Saudi index to the global market index (a_{12}) and vice versa, suggesting that the information shocks from both the Saudi indices and Brent impact each other at a 1% significance level. Significant volatility spillover from Brent to the Saudi local market is also present (b_{21}), indicating that Brent's volatility significantly affects the volatility of the Saudi market. These results suggest that the pre-reform period saw significant spillover effects between the two markets, indicating that the global market had a significant influence on the Saudi market.

The results of the Table 6.20 suggest that the Saudi stock markets are more susceptible to shocks coming from global indices such as Brent. This implies that the Saudi stock markets are more volatile and prone to shocks from the global market than are the Islamic stock indices. Thus, investors should be mindful of the global market when investing in Saudi stock markets. Additionally, it is important for policymakers to consider the effects of global markets when formulating regulations and policies to ensure stability in Saudi stock markets.

Table 6.20: Results of the bivariate VAR-GARCH BEKK (1,1) estimation for the pre-reform period between the Saudi stock indices and Brent.

	Pre-Reform Period *(04/01/2010–15/05/2015)*				
			Brent		
	IS1	**IS2**	**IS3**	**MS**	**CS**
a_{11}	0.0001	0.0104	0.2935^{***}	-0.0094	0.0082
a_{12}	0.1391^{***}	0.1402^{***}	0.0104^{**}	-0.1872^{***}	0.1479^{***}
a_{21}	-0.1382^{***}	-0.1390^{***}	-0.1287	-0.1849^{***}	-0.1242^{***}
a_{22}	0.2775^{***}	0.2697^{***}	0.2796^{***}	0.3014^{***}	0.2674^{***}
b_{11}	0.9833^{***}	0.9818^{***}	0.9470^{***}	0.9822^{***}	0.9826^{***}
b_{12}	-0.0032^{***}	-0.0051	-0.0054^{**}	-0.0070	-0.0044
b_{21}	0.1291^{***}	0.1189^{***}	0.0305^{*}	0.1134^{***}	0.1171^{***}
b_{22}	0.8932^{***}	0.9049^{***}	0.9684^{***}	0.8969^{***}	0.8987^{***}
			Diagnostic Tests		
Log L.	-4346	-4394	-3530	-4370	-4402
LBQ^2 (20)	168.2889 (1.8640e-25)	191.0157 (6.6764e-30)	0.8310 (1.0000)	198.0037 (2.7925e-31)	198.7254 (2.8496e-33)

Notes: A and B capture the shock and volatility effects, respectively. The a_{11} coefficient reflects the effect of previous shocks from the Saudi stock index on its own current shock; a_{12} indicates the ARCH effect of shocks from the local Saudi index to the global market index; a_{21} shows that cross-market shocks from the global index to the Saudi stock indices also have an ARCH effect; and a_{22} captures the impact of previous shocks from each global market on its own current shock. Then, b_{11} explores the effect of past volatility on the current conditional variance of the Saudi stock indices; b_{12} captures the volatility spillover from the Saudi stock indices to the global market; b_{21}measures the volatility spillover from the global market to the Saudi stock indices; and b_{22} captures the volatility spillover from each global index's conditional variance to its own. Further, the diagnostics tests section presents the LogL (log likelihood) for the bivariate BEKK estimation, where LBQ^2 (20) is the Ljung-BoxQ statistic up to 20 lags. Significance levels of ***, ** and * refers to the null hypothesis is rejected at 1%, 5% and 10%, respectively.

Table 6.21 presents the results of the bivariate VAR-GARCH-BEKK (1,1) estimation between the Saudi stock indices and WTI during the pre-reform period. The results indicate the significant unidirectional effect of past shocks from WTI to the Saudi stock indices, suggesting that changes in WTI can have a direct and significant impact on the Saudi stock market. Additionally, the results show a statistically significant spillover of volatility from WTI to the Saudi stock indices at a 1% confidence level. This implies that volatility in WTI can have a significant and lasting effect on the Saudi stock market. WTI's own conditional variance effect is also significant at a 1% level, indicating that changes in the index's volatility can significantly impact its own volatility.

Table 6.21: Results of the bivariate VAR-GARCH BEKK (1,1) estimation for the pre-reform period between the Saudi stock indices and WTI.

	Pre-Reform Period *(04/01/2010–15/05/2015)*				
			WTI		
	IS1	**IS2**	**IS3**	**MS**	**CS**
$\boldsymbol{a_{11}}$	0.0803	0.0799	0.2708***	0.0782	0.0858
$\boldsymbol{a_{12}}$	0.0921	0.1111*	-0.0111*	0.1152	0.1080
$\boldsymbol{a_{21}}$	-0.1019***	-0.0927***	0.0736	-0.0818***	-0.0833***
$\boldsymbol{a_{22}}$	0.2717***	0.2708***	0.2748***	0.2724***	0.2661***
$\boldsymbol{b_{11}}$	0.9865***	0.9851***	0.9530***	0.9861***	0.9854***
$\boldsymbol{b_{12}}$	-0.0090	-0.0109	0.0060*	-0.0107	-0.0112
$\boldsymbol{b_{21}}$	0.0764***	0.0735***	-0.0193	0.0712**	0.0692***
$\boldsymbol{b_{22}}$	0.9278***	0.9264***	0.9688***	0.9220***	0.9283***
			Diagnostic Tests		
Log L.	-4221	-4265	-3387	-4258	-4273
LBQ²(20)	131.6496 (1.9102e-18)	153.5642 (1.3028e-22)	0.8538 (1.0000)	157.0421 (2.7922e-23)	181.1136 (5.8761e-28)

Notes: A and B capture the shock and volatility effects, respectively. The a_{11} coefficient reflects the effect of previous shocks from the Saudi stock index on its own current shock; a_{12} indicates the ARCH effect of shocks from the local Saudi index to the global market index; a_{21} shows that cross-market shocks from the global index to the Saudi stock indices also have an ARCH effect; and a_{22} captures the impact of previous shocks from each global market on its own current shock. Then, b_{11} explores the effect of past volatility on the current conditional variance of the Saudi stock indices; b_{12} captures the volatility spillover from the Saudi stock indices to the global market; b_{21}measures the volatility spillover from the global market to the Saudi stock indices; and b_{22} captures the volatility spillover from each global index's conditional variance to its own. The diagnostic tests present the LogL (log likelihood) for the bivariate BEKK estimation, where LBQ^2 (20) is the Ljung-BoxQ statistic up to 20 lags. Significance levels of ***, ** and * indicate that the null hypothesis is rejected at 1%, 5% and 10%, respectively.

6.4.1.3 Post-Reform Period (May 2015–June 2021)

Similarly, for the post-reform period, the a_{11}, a_{22}, b_{11} and a_{22} coefficients are significant at the 1% level. This suggests that the influence of the two indices' own past values remain statistically significant. Additionally, the estimations of b_{12} and b_{21} show insignificant increases in the volatility spillover between all the Saudi indices and S&P 500, except for IS1. The estimations show bidirectional volatility spillover between IS1 and S&P 500, with significant volatility spillover from IS1 to S&P 500 (0.6290) and vice versa (-0.3386). The volatility spillover between the Saudi Islamic and conventional stock indices and the S&P 500 index increase more than the conventional indices (MS and CS) in both directions, though the results are not statistically significant (except for IS1).

The findings shown in Table 6.22 have important implications for investors, who should consider the effects of shock and volatility spillover when making investment decisions. By understanding the relationship between the Saudi stock indices and S&P 500, investors can better anticipate market changes and make more informed decisions. In addition, the volatility spillover between the Saudi stock indices and S&P 500 increase with the introduction of liberalising initiatives, and these spillovers are likely to keep increasing. This suggests that volatility spillover is an important factor to consider when analysing the performance of investments over time, and that it is essential to take these effects (reforms, Islamic stocks) into account when making investment decisions.

The results in Table 6.23 show the bivariate VAR-GARCH-BEKK estimations that investigate the shock and volatility spillover between Brent and the five Saudi stock indices. The outcomes demonstrate that the coefficients of a_{11}, a_{21} and a_{22} are all statistically significant. This suggests that both the Saudi indices and Brent have their own ARCH effects and that shock effects exist between Brent and the Saudi stock indices.

Furthermore, the conventional stock index (CS) sees a strong and consistent shock impact from Brent compared to the MS and Islamic stock indices.

The results in Table 6.23 show that IS1, IS2, IS3, MS and CS have statistically significant coefficients for b_{11} at a 1% confidence level, while MS and CS have statistically significant coefficients for b_{21}. This suggests significant volatility spillover from Brent to MS and CS, although the impact is not the same for all of them. Interestingly, the volatility spillover from Brent to the non-Islamic stock indices has a greater impact than on the Islamic counterparts, with the Islamic indices having no significant bidirectional volatility spillover, except for IS2 (0.1933). This suggests that the Saudi stock indices are affected differently by Brent shock and volatility spillover.

The results in Table 6.24 present the bivariate VAR-GARCH BEKK (1,1) estimation for the post-reform period between the Saudi stock indices and WTI. These results show that overall shocks from the local Saudi indices and WTI have an ARCH effect, as indicated by the a_{11} and a_{22} coefficients. Furthermore, cross-market shocks from the WTI to the Saudi stock indices have a significant ARCH effect, as indicated by the a_{21} coefficient, implying that IS3, MS and CS have significant evidence of shock from WTI at 10%, 5% and 10%, respectively. The results also indicate shock effects from IS1, IS3 and CS to WTI, but no significant evidence of information shock for the other indices.

Table 6.24 illustrates the bidirectional volatility spillover between all five stock indices (IS1, IS2, IS3, MS and CS) and WTI. These results reveal that during the post-reform period, significantly increased volatility spillover occurs from the Saudi stock indices to WTI compared to the pre-reform period. The b_{21} coefficient shows that the volatility spillover rates from WTI to IS1 (0.1464), IS2 (0.3591), IS3 (0.5424), MS (0.3509) and CS (0.3508) are all significant at the 1% confidence level.

The results of Table 6.24 have implications for investors in the Saudi stock market. First, they indicate that the Saudi stock market has become more sensitive to external shocks, such as those from WTI, which investors should take into account when making decisions. Second, the results suggest a significant increase in volatility spillover from Saudi stock indices to WTI, meaning that investors may need to diversify their investments to reduce risks related to price volatility. Finally, the results indicate a significant effect from WTI to the Saudi stock indices, so investors should consider WTI when making investment decisions.

Further, stock market liberalisation can increase the volatility spillover between local and global markets for a variety of reasons. First, the liberalisation of markets can lead to increased competition, which can drive up prices and increase volatility. Second, increased liquidity can lead to more rapid price movements and higher volatility. Third, the liberalisation of markets can lead to increased integration between the Saudi stock market and global markets, which can result in increased correlations and more rapid transmission of shocks and volatility across the markets. Finally, the liberalisation of stock markets can lead to higher levels of speculation, which can increase the risk associated with investing and result in higher volatility.

Table 6.22: Results of the bivariate VAR-GARCH BEKK (1,1) estimation for the post-reform periods between the Saudi stock indices and the S&P 500 index.

Post-Reform Period *(16/05/2015–29/06/2021)*					
	S&P 500				
	IS1	**IS2**	**IS3**	**MS**	**CS**
a_{11}	0.5150***	0.5539***	0.5572***	0.5244***	0.5341***
a_{12}	-0.3930	0.0192	0.0288	0.2241	0.0960
a_{21}	0.1179*	0.0469	0.0334	-0.0767	-0.0433
a_{22}	0.1346	0.2581***	0.2553**	0.2866***	0.3060***
b_{11}	0.8387***	0.8483***	0.8455***	0.8467***	0.8471***
b_{12}	0.6290***	0.1086	0.0965	-0.0974	-0.0234
b_{21}	-0.3386***	-0.1122	-0.0981	0.0307	0.0075
b_{22}	0.5792***	0.9199***	0.5572***	0.9287***	0.9384***
Diagnostic Tests					
Log L.	-3699	-3672	-3721	-3702	-3712
LBQ^2 (20)	9.4476 (0.9771)	94.2893 (1.3060e-11)	113.8722 (3.84407e-15)	116.2799 (1.3872e-15)	106.4304 (8.7509e-14)

Notes: A and B capture the shock and volatility effects, respectively. The a_{11} coefficient reflects the effect of previous shocks from the Saudi stock index on its own current shock; a_{12} indicates the ARCH effect of shocks from the local Saudi index to the global market index; a_{21} shows that cross-market shocks from the global index to the Saudi stock indices also have an ARCH effect; and a_{22} captures the impact of previous shocks from each global market on its own current shock. Then, b_{11} explores the effect of past volatility on the current conditional variance of the Saudi stock indices; b_{12} captures the volatility spillover from the Saudi stock indices to the global market; b_{21}measures the volatility spillover from the global market to the Saudi stock indices; and b_{22} captures the volatility spillover from each global index's conditional variance to its own. The diagnostic tests present the LogL (log likelihood) for the bivariate BEKK estimation, where LBQ^2 (20) is the Ljung-BoxQ statistic up to 20 lags. Significance levels of ***, ** and * indicate that the null hypothesis is rejected at 1%, 5% and 10%, respectively.

Table 6.23: Results of the bivariate VAR-GARCH BEKK (1,1) estimation for the post-reform period between the Saudi stock indices and Brent.

	Post-Reform Period *(16/05/2015–29/06/2021)*				
	Brent				
	IS1	**IS2**	**IS3**	**MS**	**CS**
a_{11}	0.3025***	0.2764***	0.2141**	0.2429***	0.2640***
a_{12}	0.2175*	0.0578	0.1427	0.0846	0.0661
a_{21}	-0.2200*	-0.2577***	-0.0891	-0.2462***	-0.2727***
a_{22}	0.2963***	0.3423***	0.3380***	0.3422***	0.3427***
b_{11}	0.9300***	0.9299***	0.9426***	0.9411***	0.9316***
b_{12}	-0.0366	-0.0132	-0.0264	-0.0195	-0.0147
b_{21}	0.1702	0.1933***	0.2749	0.2125***	0.2044***
b_{22}	0.7052***	0.9139***	0.7887***	0.8954***	0.9110***
	Diagnostic Tests				
Log L.	-5263	-5173	-5228	-5199	-5206
LBQ^2 (20)	7.6929 (0.9937)	80.0143 (3.9041e-09)	64.4781 (1.4130e-06)	73.8719 (4.1968e-08)	75.7805 (2.0181e-08)

Notes: A and B capture the shock and volatility effects, respectively. The a_{11} coefficient reflects the effect of previous shocks from the Saudi stock index on its own current shock; a_{12} indicates the ARCH effect of shocks from the local Saudi index to the global market index; a_{21} shows that cross-market shocks from the global index to the Saudi stock indices also have an ARCH effect; and a_{22} captures the impact of previous shocks from each global market on its own current shock. Then, b_{11} explores the effect of past volatility on the current conditional variance of the Saudi stock indices; b_{12} captures the volatility spillover from the Saudi stock indices to the global market; b_{21}measures the volatility spillover from the global market to the Saudi stock indices; and b_{22} captures the volatility spillover from each global index's conditional variance to its own. The diagnostic tests present the LogL (log likelihood) for the bivariate BEKK estimation, where LBQ^2 (20) is the Ljung-BoxQ statistic up to 20 lags. Significance levels of ***, ** and * refers to the null hypothesis is rejected at 1%, 5% and 10%, respectively.

Table 6.24: Results of the bivariate VAR-GARCH BEKK (1,1) estimation for the post-reform period between the Saudi stock indices and WTI.

	Post-Reform Period *(16/05/2015–29/06/2021)*				
	WTI				
	IS1	**IS2**	**IS3**	**MS**	**CS**
a_{11}	0.3405***	0.2575	0.2945***	0.2836*	0.2679**
a_{12}	0.1267**	0.0813	0.1154***	0.1062	0.0902*
a_{21}	-0.0687	-0.2413	-0.3385*	-0.2696**	-0.2632*
a_{22}	0.2398***	0.2850***	0.2437***	0.2645***	0.2771***
b_{11}	0.9081***	0.8939***	0.8509***	0.8832***	0.8896***
b_{12}	-0.0713***	-0.0658***	-0.1184***	-0.0702***	-0.0689***
b_{21}	0.1464***	0.3591***	0.5424***	0.3509***	0.3508***
b_{22}	0.9481***	0.9550***	0.9402***	0.9516***	0.9559***
	Diagnostic Tests				
Log L.	-5118	-5045	-5090	-5072	-5080
LBQ^2 (20)	24.0729 (0.2392)	76.6699 (1.4321e-08)	72.583 (6.8596e-08)	89.1375 (1.0486e-10)	83.1836 (1.1239e-09)

Notes: A and B capture the shock and volatility effects, respectively. The a_{11} coefficient reflects the effect of previous shocks from the Saudi stock index on its own current shock; a_{12} indicates the ARCH effect of shocks from the local Saudi index to the global market index; a_{21} shows that cross-market shocks from the global index to the Saudi stock indices also have an ARCH effect; and a_{22} captures the impact of previous shocks from each global market on its own current shock. Then, b_{11} explores the effect of past volatility on the current conditional variance of the Saudi stock indices; b_{12} captures the volatility spillover from the Saudi stock indices to the global market; b_{21}measures the volatility spillover from the global market to the Saudi stock indices; and b_{22} captures the volatility spillover from each global index's conditional variance to its own. The diagnostic tests present the LogL (log likelihood) for the bivariate BEKK estimation, where LBQ^2 (20) is the Ljung-BoxQ statistic up to 20 lags. Significance levels of ***, ** and * refers to the null hypothesis is rejected at 1%, 5% and 10%, respectively.

6.4.1.4 COVID-19 Effect

The COVID-19 pandemic has had a powerful, far-reaching impact on the global economy, leading to unprecedented levels of financial market volatility. Oil markets have been profoundly affected, with a dramatic drop in prices due to reduced global demand. As such, this study seeks to investigate the effect of COVID-19 on volatility spillover between global markets (Brent, WTI and S&P 500) and Saudi stock indices. Therefore, the study considers the current state of the oil market (Brent and WTI) and its implications for the Saudi stock market, the impact of COVID-19-induced volatility spillover between the global market and the Saudi stock indices, and how the event has interpreted liberalisation reforms in the Saudi stock market.

In Table 6.25, the results of the bivariate VAR-GARCH-BEKK (1,1) estimation between the Saudi stock indices and S&P 500 for the COVID-19 period reveal that the a_{11} coefficient, which reflects the influence of previous shocks from the Saudi stock index on its own current shock, is statistically significant at 1%. The a_{12} coefficient highlights the ARCH effect of shocks from the local Saudi index on S&P 500, significant at 1%. The a_{21} coefficient indicates that the cross-market shocks from S&P 500 also have an ARCH effect on the Saudi stock indices, significant at 5%. The a_{22} coefficient shows the impact of previous shocks from the S&P 500 on its own current shock, significant at 1%.

Table 6.25 shows that the b_{11} coefficient explores the effect of past volatility on the current conditional variance of the Saudi stock indices, significant at 10%. Both the b_{12} and b_{21} coefficients capture the volatility spillover between the Saudi stock indices to the S&P 500, where only IS3 and CS are significant at 1%. Finally, the b_{22} coefficient measures the volatility spillover from the S&P 500 index's conditional variance to its own, which is significant at a 1% confidence level.

Table 6.26 and Table 6.27 show the results of the bivariate VAR-GARCH-BEKK estimations concerning the spillover of shock and volatility between the oil commodity market and the Saudi stock indices during COVID-19. Overall, the results indicate that the Saudi stock indices tend to have higher coefficients with WTI estimation than with Brent, which suggests that the Saudi stock indices are more sensitive to shocks and volatility from WTI than from Brent. Additionally, the CS index has the highest b_{11}

coefficient, followed by the IS1, IS2, IS3 and MS indices. Similarly, the IS1 index has the highest b_{12} coefficient, followed by the IS2, IS3, MS and CS indices. Lastly, the IS2 index has the highest b_{21} coefficient, followed by the IS1, IS3, MS and CS indices.

As shown in Table 6.25, Table 6.26 and Table 6.27, the results of the diagnostic tests for the bivariate VAR-GARCH-BEKK estimation differ across all indices. IS1 and IS2 have the highest results, and IS3, MS and CS have the lowest. However, none of the model estimations are statistically significant. This can be attributed to the small sample size (340 observations), which is not large enough to estimate the parameters of the model accurately and reliably. Several studies have established that a sample size of at least 500 observations is necessary for GARCH models, and 1,000 observations is recommended for simple GARCH models (Hwang & Pereira 2006; Ng & Lam 2006). This indicates that the small sample size present in this study likely impacted the reliability and accuracy of the results.

Table 6.25: Results of the bivariate VAR-GARCH-BEKK (1,1) estimation between the Saudi stock indices and S&P 500 during the COVID-19 period.

	COVID-19 Period *(11/03/2020–29/06/2021)*				
	S&P 500				
	IS1	**IS2**	**IS3**	**MS**	**CS**
a_{11}	0.0965***	0.2030**	-0.1283***	0.5486***	0.2494***
a_{12}	-0.0811***	-0.0761	-0.0728***	0.0433	0.2141***
a_{21}	-0.0192	-0.0806	0.0295	-0.0818	0.1746***
a_{22}	0.2476***	0.2205***	0.2472***	-0.0888	0.1549***
b_{11}	0.3476	0.6330	0.0420	0.7796***	0.8670***
b_{12}	-0.2449	-0.2069	-0.1508***	-0.0554	0.0744***
b_{21}	-0.1980	-0.2629	0.0599***	0.0288	0.0759***
b_{22}	0.8744***	0.7661***	0.9688***	0.7986***	0.7598***
	Diagnostic Tests				
Log L.	-5460	-5668	-5400	-6474	-6264
LBQ^2 (20)	0.0309 (1.0000)	0.0215 (1.0000)	0.1561 (1.0000)	0.0158 (1.0000)	0.0172 (1.0000)

Notes: A and B capture the shock and volatility effects, respectively. The a_{11} coefficient reflects the effect of previous shocks from the Saudi stock index on its own current shock; a_{12} indicates the ARCH effect of shocks from the local Saudi index to the global market index; a_{21} shows that cross-market shocks from the global index to the Saudi stock indices also have an ARCH effect; and a_{22} captures the impact of previous shocks from each global market on its own current shock. Then, b_{11} explores the effect of past volatility on the current conditional variance of the Saudi stock indices; b_{12} captures the volatility spillover from the Saudi stock indices to the global market; b_{21}measures the volatility spillover from the global market to the Saudi stock indices; and b_{22} captures the volatility spillover from each global index's conditional variance to its own. The diagnostic tests present the LogL (log likelihood) for the bivariate BEKK estimation, where LBQ^2 (20) is the Ljung-BoxQ statistic up to 20 lags. Significance levels of ***, ** and * refers to the null hypothesis is at 1%, 5% and 10%, respectively.

Table 6.26: Results of the bivariate VAR-GARCH BEKK (1,1) estimation between the Saudi stock indices and Brent during the COVID-19 period.

	COVID-19 Period *(11/03/2020–29/06/2021)*				
	Brent				
	IS1	**IS2**	**IS3**	**MS**	**CS**
a_{11}	0.7196***	0.6947**	0.0499***	0.3344***	0.2935***
a_{12}	0.0493	0.0335	-0.7559***	0.0481	-0.0417**
a_{21}	-0.2400**	-0.2164	-0.0004***	0.4039***	-0.5045***
a_{22}	0.3502***	0.3862***	0.0507***	0.0632*	0.0808*
b_{11}	0.7762***	0.7991***	0.4838***	0.9178***	0.9216***
b_{12}	0.0009	0.0057	-0.0064***	0.0041	-0.0014
b_{21}	0.0426	0.0745	-0.0004***	0.1752	-0.1408
b_{22}	0.8793***	0.8608***	0.4449***	0.7575	0.8178***
	Diagnostic Tests				
Log L.	-6767	-6891	-7111	-7323	-6945
LBQ²(20)	0.0319 (1.0000)	0.0210 (1.0000)	0.1482 (1.0000)	0.0160 (1.0000)	0.0170 (1.0000)

Notes: A and B capture the shock and volatility effects, respectively. The a_{11} coefficient reflects the effect of previous shocks from the Saudi stock index on its own current shock; a_{12} indicates the ARCH effect of shocks from the local Saudi index to the global market index; a_{21} shows that cross-market shocks from the global index to the Saudi stock indices also have an ARCH effect; and a_{22} captures the impact of previous shocks from each global market on its own current shock. Also, b_{11} explores the effect of past volatility on the current conditional variance of the Saudi stock indices; b_{12} captures the volatility spillover from the Saudi stock indices to the global market; b_{21}measures the volatility spillover from the global market to the Saudi stock indices; and b_{22} captures the volatility spillover from each global index's conditional variance to its own. The diagnostic tests present the LogL (log likelihood) for the bivariate BEKK estimation, where LBQ^2 (20) is the Ljung-BoxQ statistic up to 20 lags. Significance levels of ***, ** and * refers to the null hypothesis is rejected at 1%, 5% and 10%, respectively.

Table 6.27: Results of the bivariate VAR-GARCH BEKK (1,1) estimation between the Saudi stock indices and WTI during the COVID-19 period.

	COVID-19 Period *(11/03/2020–29/06/2021)*				
			WTI		
	IS1	**IS2**	**IS3**	**MS**	**CS**
a_{11}	2.8180***	0.0436***	3.5554***	2.5608***	0.1969
a_{12}	-0.4767***	-0.4532***	-0.2881***	-1.8357***	-0.0773
a_{21}	-2.2942***	-0.0049***	-1.4929*	-1.8464***	-0.3341
a_{22}	0.6915***	0.0490***	0.3807***	1.8592***	0.1415
b_{11}	0.0540***	0.4300***	0.1510***	0.3937***	0.8590***
b_{12}	0.1681***	0.0001	0.0702***	0.4505***	-0.0460***
b_{21}	0.2874***	-0.0009*	0.0365	0.6039***	-0.2992
b_{22}	0.9001***	0.4731***	0.9523***	0.4416***	0.7361***
			Diagnostics Tests		
Log L.	-5588	-8152	-5556	-6054	-6860
LBQ^2 (20)	0.1088 (1.0000)	0.2177 (1.0000)	1.7954 (1.0000)	0.1388 (1.0000)	0.1471 (1.0000)

Notes: A and B capture the shock and volatility effects, respectively. The a_{11} coefficient reflects the effect of previous shocks from the Saudi stock index on its own current shock; a_{12} indicates the ARCH effect of shocks from the local Saudi index to the global market index; a_{21} shows that cross-market shocks from the global index to the Saudi stock indices also have an ARCH effect; and a_{22} captures the impact of previous shocks from each global market on its own current shock. Then, b_{11} explores the effect of past volatility on the current conditional variance of the Saudi stock indices; b_{12} captures the volatility spillover from the Saudi stock indices to the global market; b_{21}measures the volatility spillover from the global market to the Saudi stock indices; and b_{22} captures the volatility spillover from each global index's conditional variance to its own. The diagnostics tests present the LogL (log likelihood) for the bivariate BEKK estimation, where LBQ^2 (20) is the Ljung-BoxQ statistic up to 20 lags. Significance levels of ***, ** and * refers to the null hypothesis is rejected at 1%, 5% and 10%, respectively.

6.5 Portfolio Management Implications

The results of the bivariate VAR-GARCH-BEKK analysis between the Saudi stock indices and the global markets suggest that there are potential opportunities for portfolio diversification through investments in both the Saudi stocks and global markets (oil or US stock market). To reduce risk exposure and wild price swings, portfolio managers must determine the optimal weights and hedging ratios to minimise additional risks without sacrificing expected returns. Investors can also achieve greater diversification gains by investing in both the local Saudi stocks and US stocks or oil commodity markets. This study investigates the implications of these volatility spillover empirical findings on optimal portfolio design and risk hedging.

This study also examines the implications of the volatility spillover findings by computing the optimal portfolio weights and hedge ratios for the full sample period (04/01/2010 to 29/06/2021) and two sub-samples (pre- and post-reform). The results of this analysis can provide investors with valuable insights on how to assess the risk levels of different Saudi stocks, based on the IFP, global oil and US stock markets, so that they can make more informed investment decisions.

6.5.1 Optimal Portfolio Weights and Hedge Ratios

This section presents the outcomes of the optimal portfolio weight computations, which use the approach described by Kroner and Ng (1998), and the hedge ratio computations for the portfolio derived using Kroner and Sultan’s (1993) technique. Both are displayed in Table 6.28, **Figure 6.3**, **Figure 6.4**, and **Figure 6.5**. The objective when constructing an optimal portfolio is to reduce risk while maximising expected returns between one of the Saudi stock indices (IS1, IS2, IS3, MS or CS) and one of the other major global markets (Brent, WTI or S&P 500). Such a hedge ratio can provide recommendations on how to reduce the risk of a Saudi stock and global market portfolio when a long position of 1000$ is hedged with a short position.[28] Table 6.28 presents the average values of the optimal portfolio weights and the hedge ratio of the combined Saudi and global portfolio for the full sample, pre-reform and post-reform periods.

The results of the full sample, shown in Table 6.28, indicate that when combining Saudi stocks with other global markets, the highest portfolio weighting for Saudi assets is found in a Saudi index and Brent oil portfolio. Here, 850$ to 860$ are allocated to Saudi stocks and 140$ to 150$ to Brent oil. The lowest portfolio weighting for Saudi assets is in a Saudi and S&P 500 portfolio, with 450$ to 500$ allocated to the Saudi indices and 500$ to 550$ to the S&P 500. This suggests that investors should hold more Saudi stocks than oil when investing in both oil and Saudi markets, but they should hold fewer Saudi assets when investing in a combined Saudi and S&P 500 portfolio to reduce the portfolio's risk without decreasing its expected return.

The results also show that the hedge ratios for the Brent oil market are 32%, 45% and 41% for IS1, IS2 and IS3, respectively. The hedge ratios for MS and CS are 28% and 35%, respectively. Similarly, the hedge ratios for the WTI oil market are 25%, 31%, 95%, 31% and 30% for IS1, IS2, IS3, MS and CS, respectively. Lastly, the hedge ratios for the Saudi and S&P 500 portfolio are 21%, 23%, 33%, 23% and 23% for IS1, IS2, IS3, MS and CS, respectively. This highlights that overall, the highest Saudi hedge ratio is in the Brent/Saudi portfolio is MS, whereas the IS3 has the highest hedge ratio in Saudi/WTI portfolios. The lowest hedge ratio is that of the S&P 500/Saudi stocks. Should an investor

[28] This analysis is interpreted to offer a recommendation to divide a 1000$ portfolio among the Saudi stock indices of IS1, IS2, IS3, MS or CS and the global markets of Brent, WTI or S&P 500.

wish to hedge a 1000$ long position in IS1, they could do so by shorting 320$, 250$ and 210$ in Brent, WTI or S&P 500, respectively.

The results in Table 6.28 indicate that the optimal portfolio weights and hedge ratios differ between the pre-reform and post-reform periods. In the pre-reform period, the optimal weights for the IS1/Brent, IS2/Brent, MS/Brent and CS/Brent portfolios were 800$, 790$, 780$ and 810$, respectively. The corresponding hedge ratios were 13%, 14%, 22% and 24%, respectively. In the post-reform period, the optimal weights for the IS1/Brent, IS2/Brent, MS/Brent and CS/Brent portfolios were 870$, 890$, 870$ and 870$, respectively. The corresponding hedge ratios were 68%, 46%, 45% and 60%, respectively. This implies an overall increase in the optimal weights for the Saudi assets in the Saudi stock/Brent portfolios, as well as an increase in the hedge ratios during the post-reform period.

In contrast to Brent, the results for the IS1/WTI, IS2/WTI, MS/WTI and CS/WTI portfolios in the pre-reform period were 760$, 750$, 750$ and 750$, respectively, and the corresponding hedge ratios were 12%, 14%, 14% and 13%, respectively. In the post-reform period, the optimal weights for the IS1/WTI, IS2/WTI, MS/WTI and CS/WTI portfolios were 670$, 560$, 560$ and 650$, respectively, and the corresponding hedge ratios were 33%, 44%, 44% and 35%, respectively. This suggests a reduction in Saudi stock index weights in the WTI/Saudi portfolios and an increase in hedging ratios when shorting in WTI.

The S&P 500/Saudi stock results show similar outcomes to the Brent/Saudi stock portfolios. For the IS1/S&P 500, IS2/S&P 500, MS/S&P 500 and CS/S&P 500 portfolios in the pre-reform period, the optimal weights were 530$, 1000$, 700$ and 510$, respectively, and the corresponding hedge ratios were 20%, 133%, 44% and 21%, respectively. In the post-reform period, the optimal weights for the IS1/S&P 500, IS2/S&P 500, MS/S&P 500 and CS/S&P 500 portfolios were 800$, 770$, 770$ and 780$, respectively. The corresponding hedge ratios were 20%, 23%, 23% and 22%, respectively, suggesting that investors should reduce hedging ratios during post-reform periods.

In the context of Islamic versus conventional stocks, Table 6.28 highlights the similarities and differences in the optimal weights and hedge ratios between the Islamic, mixed and conventional stock indices in the full sample period. For Brent/Saudi stock portfolios, the Islamic stocks have higher hedge ratios compared to MS and CS, thereby providing greater protection against market volatility. The WTI/IS3 and S&P 500/IS3 combinations have the highest hedging percentages among the other Saudi/WTI or Saudi/S&P 500 portfolios, indicating their effectiveness in mitigating market risks. These findings suggest that when constructing portfolios, Islamic stocks may need to short more in other markets than their conventional counterparts.

During the post-reform period, the Brent/Islamic stock hedge ratio increased, even if not as significantly as other, more confidential portfolios. The results regarding the WTI/Saudi stock hedge ratio are mixed, while the S&P 500/Saudi stock hedge ratio presents a contradiction between the Islamic stock index and other indices. Specifically, the Islamic stock/S&P 500 ratio decreased in value, while MS and CS experienced a slight rise. This suggests that the Islamic stock index is less affected by the post-reform period than the other indices, which could point to an overall decrease in the risk associated with investing in Islamic stocks.

Figure 6.3: Time-varying hedge ratios of Brent and Saudi stock indexes computed from bivariate GARCH model for the full period (January 2010–June 2021).

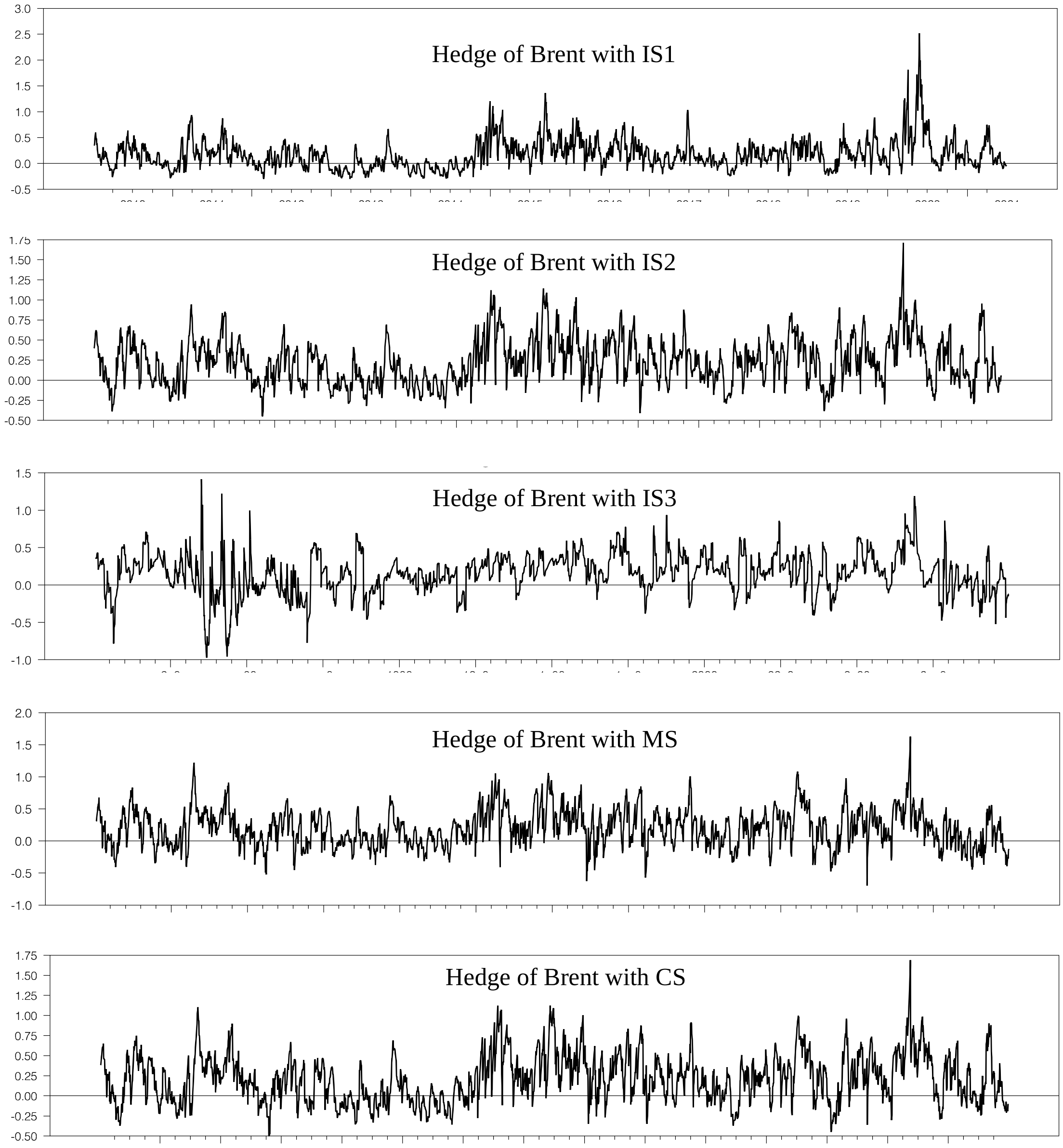


Figure 6.4: Time-varying hedge ratios of WTI and Saudi stock indexes computed from bivariate GARCH model for the full period (January 2010–June 2021).

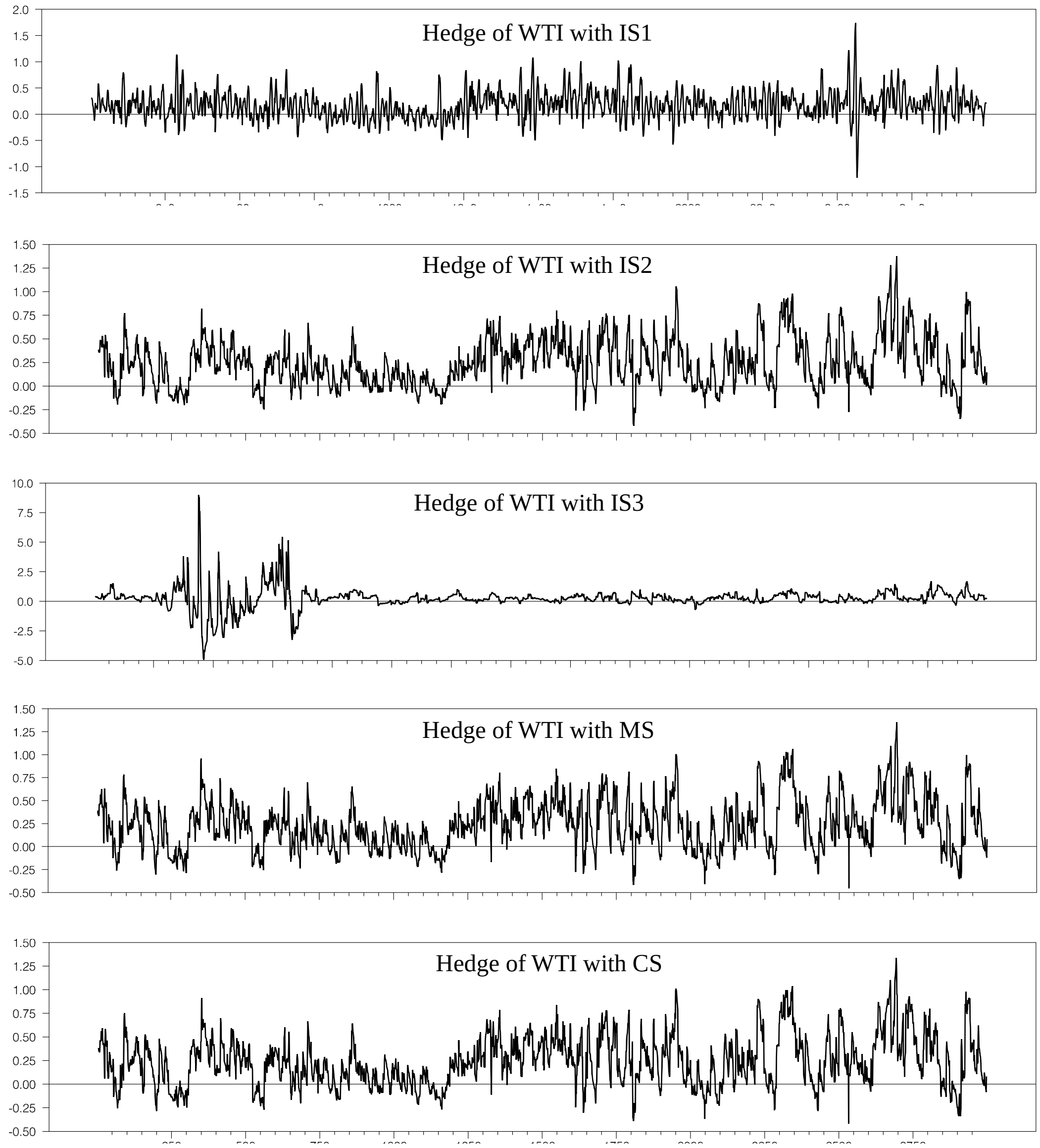


Figure 6.5: Time-varying hedge ratios of S&P500 and Saudi stock indexes computed from bivariate GARCH model for the full period (January 2010–June 2021).

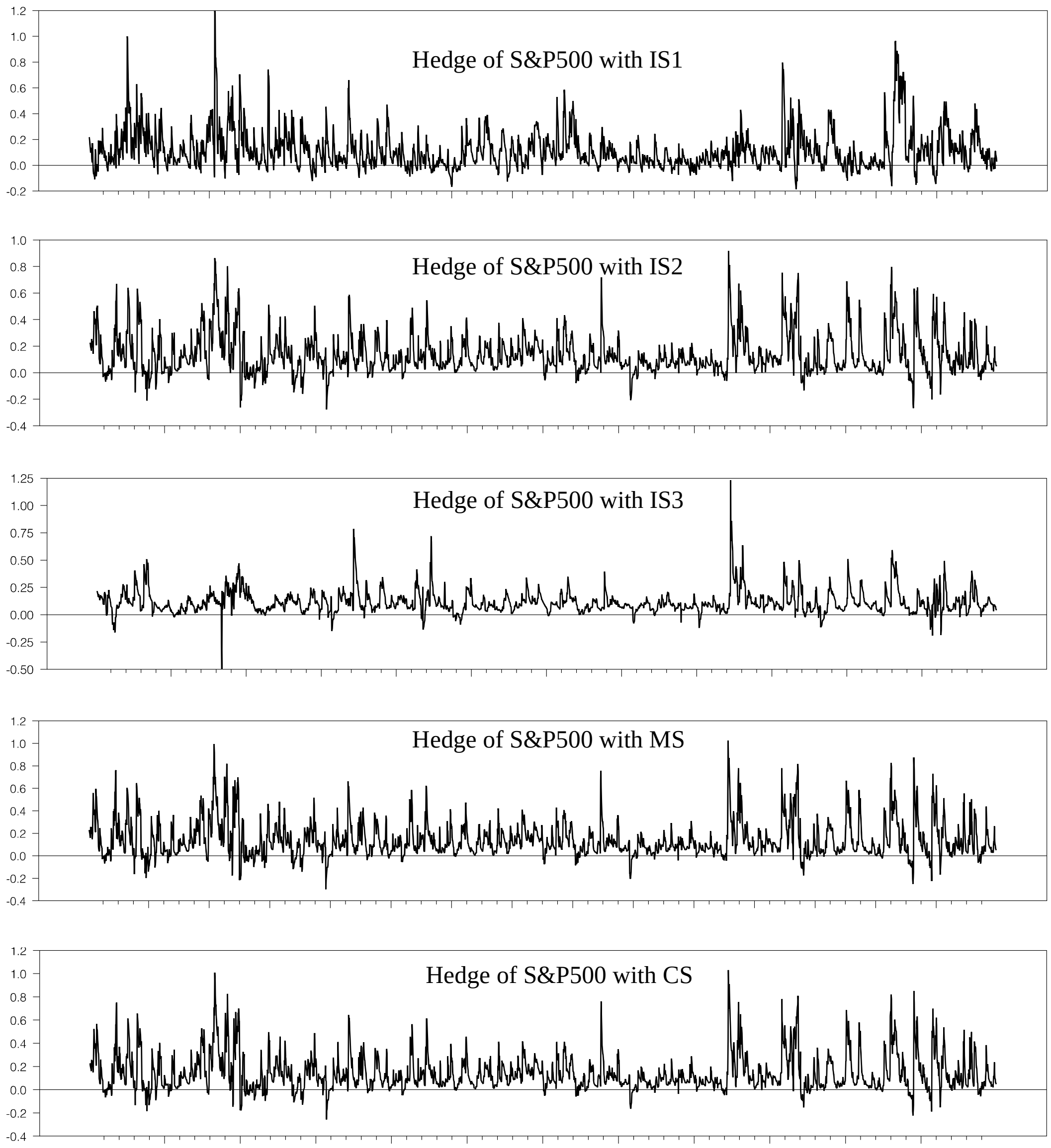


Table 6.28: Results of optimal portfolio weights and hedge ratios for the Saudi stock indices and global markets.

Portfolios	**Full Sample**		**Pre-Reform Period**		**Post-Reform Period**	
	$W_{j\text{-}i}$	$\beta_{j\text{-}i}$	$W_{j\text{-}i}$	$\beta_{j\text{-}i}$	$W_{j\text{-}i}$	$\beta_{j\text{-}i}$
Brent/IS1	0.15	0.32	0.20	0.13	0.13	0.68
Brent/IS2	0.14	0.45	0.21	0.14	0.11	0.46
Brent/IS3	0.14	0.41	0.12	0.33	0.13	0.35
Brent/MS	0.15	0.28	0.22	0.22	0.13	0.45
Brent/CS	0.14	0.35	0.19	0.24	0.13	0.60
WTI/IS1	0.18	0.25	0.24	0.12	0.15	0.33
WTI/IS2	0.18	0.31	0.25	0.14	0.12	0.44
WTI/IS3	0.14	0.95	0.14	0.28	0.15	0.39
WTI/MS	0.17	0.31	0.25	0.14	0.12	0.44
WTI/CS	0.18	0.30	0.25	0.13	0.15	0.35
S&P 500/IS1	0.55	0.21	0.47	0.20	0.65	0.20
S&P 500/IS2	0.55	0.23	0.00	1.33	0.61	0.23
S&P 500/IS3	0.50	1.33	0.30	0.44	0.63	0.21
S&P 500/MS	0.55	0.23	0.47	0.19	0.63	0.23
S&P 500/CS	0.55	0.23	0.49	0.21	0.65	0.22

Note: This table displays the sample period's average optimal portfolio weights and hedge ratios. $W_{j\text{-}i}$ refers to the weights of the portfolio, which consists of i (*i= IS1, IS3, IS3, MS, or, CS*) and j (*j= Brent, WTI, or S&P 500*). $\beta_{i\text{-}j}$ indicates the hedge ratios.

6.6 Conclusion

This chapter presents the findings of the investigation into volatility spillover between five Saudi stock indices, categorised to address IFP, the oil market (Brent and WTI) and the US stock market (S&P 500). This study applied three time series techniques for this purpose; namely, ARMA-GARCH, CCF and VAR-GARCH-BEKK. This format was designed to offer thorough empirical evidence related to volatility spillover, liberalisation reform, the COVID-19 pandemic and market segmentation based on Islamic social norms.

First, the results of the ARMA-GARCH (1,1) estimation suggest that the liberalisation of the Saudi stock market has significantly impacted the volatility spillover between the different markets, with the volatility spillover increasing in the post-reform period. This increase in spillover was most prominent between the Islamic stock indices (IS1, IS2 and IS3) and global markets (Brent, WTI and S&P 500), suggesting the existence of market segmentation based on IFP. The reforms may have increased the liquidity of the Islamic stock markets, reduced regulatory complexity and improved transparency and disclosure, resulting in increased capital flows and investor confidence.

Second, the outcomes of the CCF test indicate a causal relationship between the Saudi stock index (IS1, IS2, IS3, MS or CS) and one global market (Brent, WTI or S&P 500) in terms of volatility spillover. The variance of the Brent return was found to significantly cause variance in the MS and CS returns, more so than the Islamic indices at lag 0 and lag 1. Similarly, the variances of WTI and S&P 500 were found to cause variances in all the Saudi stock index returns at lag 0 and lag 1, with increased lag and lead values during the post-liberalisation period. The CCF test results support the previous ARMA-GARCH estimation outcomes and suggest an increased volatility spillover effect between the local Saudi stock indices and global markets in the post-reform period.

Third, the study utilised a bivariate VAR-GARCH-BEKK approach to examine the volatility and cross-volatility spillover among the Saudi stocks indices and selected global markets. The results indicate that the Saudi stock indices react positively to changes in the oil market and US stock market, implying that these markets have a profound influence on the Saudi market. The Islamic and mixed stock indices have a stronger correlation to the oil market and US stock market compared to the non-Islamic index. Additionally, the findings demonstrate that the US stock market is an important source of information shock and volatility spillover to the Saudi stock market. The overall results suggest that investors in the Saudi stock market should pay close attention to the oil and US stock market to better understand the dynamics of their investments.

The pre-reform period (2010 to 2015) indicates the significant effect of both own past shock (ARCH) and own past volatility (GARCH) for both the Saudi stock indices (IS1, IS2, IS3, MS and CS) and S&P 500. However, there was no evidence of shock and volatility spillover between the Saudi stock indices and S&P 500 during this period. Additionally, the bivariate VAR-GARCH-BEKK (1,1) estimations for the pre-reform period between the Saudi stock indices and Brent and WTI revealed a significant ARCH effect from the local Saudi index to the global market index (a12), and vice versa, as well as a significant volatility spillover from Brent and WTI to the Saudi local market (b21). These results suggest that the pre-reform period saw significant spillover effects between the Saudi stock indices and Brent/WTI, indicating that the global market significantly influenced the Saudi market. Moreover, it suggests that the Saudi stock markets are more volatile and prone to shocks from the global market compared to the Islamic stock indices.

Investors should therefore be mindful of the global market when investing in Saudi stock markets, and policymakers should consider the effects of global markets when formulating regulations and policies to ensure stability in the Saudi stock markets.

The liberalisation of the Saudi stock market has had a significant impact on the shock and volatility spillover between the Saudi stock indices and global markets such as S&P 500 and Brent/WTI. The results of the bivariate VAR-GARCH-BEKK estimations indicate that the Saudi stock indices are more sensitive to external shocks and volatility spillover, particularly from S&P 500 and WTI. The results also indicate that the volatility spillover from the Saudi stock indices to the global markets increased significantly during the post-reform period; investors should take this into account when making investment decisions. Additionally, the results show that WTI has a significant impact on the volatility of the Saudi stock indices, so investors should consider this when making investment decisions.

The COVID-19 pandemic also had a significant effect on the global markets, particularly oil, where dramatic price drops occurred because of reduced demand. This study analysed the impact of the pandemic on the volatility spillover between the global markets (Brent, WTI and S&P 500) and the Saudi stock indices. Results of the bivariate VAR-GARCH-BEKK (1,1) estimation for the COVID-19 period revealed that the coefficients for the Saudi stock indices and S&P 500 are generally significant. Additionally, the Saudi stock indices tend to have higher coefficients with WTI than with Brent. However, the small sample size of 340 observations likely impacted the accuracy of the results.

Finally, the results of the optimal portfolio weighting and hedge ratio investigations of the Saudi/global portfolios during the full sample, pre-reform and post-reform periods suggest that investors should hold more Saudi stocks than oil when investing in both oil and Saudi markets, and fewer Saudi assets when investing in a Saudi/S&P 500 portfolio, to reduce the portfolio’s risk without decreasing its expected return. The highest portfolio weighting for Saudi assets was found in a Saudi indices/Brent oil portfolio, while the lowest portfolio weighting for Saudi assets was in a Saudi/S&P 500 portfolio. In comparison, the pre-reform and post-reform periods have seen an increase in the optimal weights for the Saudi assets in Saudi stock/Brent portfolios, as well as an increase in hedge ratios during the post-reform period. Meanwhile, the results for the WTI/Saudi stock hedge ratios are mixed, while the S&P 500/Saudi stock hedge ratios present a contradiction between the Islamic stock index and the other indices. These findings suggest that Islamic stocks may need to short more in other markets compared to their conventional counterparts, and that the Islamic stock index has been less affected by the post-reform period compared to the other indices.

CHAPTER 7: CONCLUSIONS AND RECOMMENDATIONS

7.1 Introduction

This chapter concludes the investigation into the impact of liberalisation reforms on the return and volatility behaviours of the Saudi stock market in the context of Islamic financial principles, which segment the market into three categories: Islamic, mixed and non-Islamic (conventional) stocks. This chapter provides a brief overview of the context of this study, the conducted research objectives, the outcomes of the empirical analyses and the policy implications of the observed changes for Saudi financial markets and investor portfolios.

This chapter presents a comprehensive summary of the study's context in Section 7.1. Section 7.2 then outlines the four objectives of the study and presents its key findings. Section 7.3 discusses the policy implications of the research. Section 7.4 identifies the study's limitations and outlines potential areas for further research. Section 7.5 concludes the chapter.

7.2 Main Objectives and Key Findings

This section addresses the four main research objectives (questions) of the study to better understand the impact of financial liberalisation reforms on the Saudi stock market in terms of risk-adjusted performance, volatility patterns, global market spillover and implications for portfolios. The key findings have been summarised to provide a comprehensive overview of the impact of the reforms.

7.2.1 First Objective

Have the Saudi stock market reforms changed the performance of three stocks based on Islamic principles?

To address this objective, descriptive statistics were used to gain an understanding of the data set, including the overall characteristics and ranges of the indices. Descriptive statistics revealed the mean, median, mode, variance and standard deviation of the data, which allowed us to make comparisons and draw meaningful conclusions. Furthermore, the results of the risk-adjusted performance analysis that used SR, TR, VaR and CVaR provided comprehensive answers.

7.2.1.1 Summary of Performance Analysis

Descriptive statistics were essential to understanding and interpreting the data in this study. The study used the daily closing prices for return/risk from 04 January 2010 to 29 June 2021 (the full sample period) to evaluate the selected stock indices. The highest returns (means) of the daily Islamic stock indices' returns during the full sample period were IS2 (3.53%), IS3 (2.12%) and IS1 (1.97%). The risks were IS1 (1.1184%), IS2 (1.1175%) and IS3 (1.0345%). These results suggest that IS1 is a higher risk and lower return investment; IS2 is a higher return and higher risk investment; and IS3 is a higher return and lower risk investment. As such, investors may prefer IS3.

When comparing the mixed and conventional (non-Islamic) indices, the study observed a risk of CS (1.1357%) and MS (1.1235%) and a return of CS (3.25%) and MS (1.97%). Concerning the risk/return ratio between the two indices, MS seems to be risker than CS. As such, investors may prefer MS over CS.

In terms of global indices, the highest return was observed for S&P 500 (4.61%), followed by Brent (1.64%) and WTI (1.02%). The highest risk was associated with Brent (2.5822%) and WTI (2.1623%), with the S&P 500 index showing the lowest risk at 1.0758%. This indicates that S&P 500 may be the preferred choice because it has both a high return and low risk.

In the context of the overall results, the obtained returns were as follows: S&P 500 (4.61%), IS2 (3.53%), CS (3.25%), IS3 (2.12%), IS1 (1.97%), MS (1.97%), Brent (1.64%) and WTI (1.02%). Brent (2.5822%) and WTI (2.1623%) had the highest risks, followed by CS (1.1357%), MS (1.1235%), IS1 (1.1184%), IS2 (1.1175%), S&P 500 (1.0758%) and IS3 (1.0345%). S&P 500 had the highest returns and the lowest risk compared to the Brent and WTI oil markets, which had low returns and high risk. CS and MS had medium returns with high risk compared to the Islamic stock indices. These results indicate that Islamic stock indices have slightly lower risk compared to mixed and conventional stock indices in the full study sample (Medhioub & Chaffai 2019).

The pattern of historical returns did not follow a normal distribution; rather, it showed a positive/negative skewness instead. The skewness of the Saudi daily index returns was negative for all the data sets, which suggests that the asymmetric tail goes more towards negative values than positive values in Saudi stock indices (Arouri et al. 2011; Medhioub & Chaffai 2019; Alsharif 2020). In terms of the skewness for Islamic, mixed and conventional (non-Islamic) stock indices, the Islamic stocks had the highest negative skewness, implying higher expected returns and large losses. Investors with a risk-averse strategy may prefer the mixed and conventional (non-Islamic) stock indices (Litzenberger 1976; Amaya et al. 2015).

As shown in Table 7.1, the overall results of the comparison between the pre- and post-reform periods showed that, on average, returns for the IS1, IS2, IS3, MS and CS indices decreased during the post-reform period, while the average returns of Brent, WTI and S&P 500 increased (see Table 5.1). Additionally, the risks (standard deviations) of all the indices' returns increased in the post-reform period. As described by Yousaf et al. (2022), this could be attributed to the increased unpredictability and volatility of the Saudi stock index returns due to declines in oil prices, which contribute to a wider range of returns that are less predictable and riskier. These results are supported by the decline in skewness observed for the Saudi stock indices, which became more negative in the post-reform period. Demonstrably, rational investors should consider the returns and risks associated with liberalisation in the Saudi stock market.

Risk-adjusted measures may be conducted to assess the performance of five Saudi stock indices (IS1, IS2, IS3, MS and CS) with consideration for associated risks. This approach allows investors to compare investments with different levels of return and risk, as both are considered when evaluating performance. Various methods, such as SR, TR, VaR and CVaR, are used to conduct the risk-adjusted performance analysis. This allows investors to compare investments with different levels of return and risk, and to better understand the performance of the different indices in the context of risk during different time periods (pre- and post-reform).

Table 7.1 summarises the Saudi stock indices' performance pre- and post-reform. The mean, SR, TR, VaR and CVaR measures of each index were all calculated for the pre-reform and post-reform periods. The overall results of the analysis show that all five indices decreased in the post-reform period. This indicates that the reforms affected the performance of the Saudi stock indices.

All five stock indices decreased in value during the post-reform period. IS1 decreased the most, dropping from 3.24% to 0.87%. Other indices, such as IS2, MS and CS also decreased, while IS3 experienced the smallest decrease from 2.70% to 1.61%. Overall, the reforms affected all the Saudi stock indices, thereby reducing their value during the post-reform period. This could be due to the allowance of QFIIs into the local market (investor-base broadening hypothesis), which resulted in more rational pricing than in the pre-reform period, when local individual traders were prominent (Chiang et al. 2011).

Table 7.1 shows the SRs of various stock indices pre- and post-reform. The SR measured how much excess returns the indices provided compared to risk; here, a higher ratio indicates a better performance. Table 7.1 shows that SR decreased across all the indices during the post-reform period, meaning the stock indices returned less than their associated risks. This suggests that the reforms negatively affected the performance of the Saudi stock market due to stock return bubbles caused by individual investors' sentiments pre-reform (Chiang et al. 2011). IS2 performed better than all other stock indices during this period.

All five stock indices experienced a decline in their Treynor ratios (TRs) post-reform, indicating that the risk-adjusted performance of the indices was poorer after liberalisation compared to before. IS1 experienced a decrease of 0.0422 to 2.26%; IS2 fell from 5.97% to 3.49%; IS3 decreased from 0.14% to -0.11%; MS fell from 4.63% to 2.12%; and CS decreased from 4.90% to 2.15%. These findings indicate the influence of QFIIs on post-reform stock price corrections due to the price bubble formed by the lottery-like behaviours of individual investors during the pre-reform period (Singh & Roca 2021). Like in the SR outcomes, IS2 performed better than all the other stock indices in the Saudi markets.

The IS1, IS3 and MS indices showed slight increases in VaR post-reform, whereas the IS2 and CS indices slightly decreased in VaR. Overall, the VaR values for all three indices increased, with the biggest increase seen in the IS3 index. This implies that the probability of potential loss post-reform increased for IS1, IS3 and MS. Table 7.1 illustrates how CVaR declined post-reform, with the IS1 index decreasing the most from 2.69% pre-reform to 0.06% post-reform. IS2 decreased from 3.61% pre-reform to 0.34% post-reform; IS3 increased from 0.40% pre-reform to 1.56% post-reform; MS decreased from 2.37% pre-reform to 0.95% post-reform; and CS decreased from 2.50% pre-reform to 1.04% post-reform. Overall, the liberalisation reforms significantly impacted all CVaR, resulting in reductions. This supports findings from previous risk-adjusted measures (return, risk, SR and TR), namely that the Saudi stock indices performed better in the pre-reform period due to price bubbles created by individual traders who drove up stock prices. The participation of QFIIs may correct the overpriced assets in the stock market post-reform (Liao et al. 2011).

Table 7.1: Summary results of performance analysis of the Saudi stock indices.

Return			
Indices	Pre-reform	Post-reform	Change in Performance
IS1	3.24%	0.87%	Decrease
IS2	4.45%	2.74%	Decrease
IS3	2.70%	1.61%	Decrease
MS	3.28%	0.83%	Decrease
CS	4.35%	2.30%	Decrease
Risk (Standard Deviation)			
Indices	Pre-reform	Post-reform	Change in Performance
IS1	1.0101%	1.2046%	Increase
IS2	1.0493%	1.1737%	Increase
IS3	0.8127%	1.1940%	Increase
MS	1.0467%	1.1862%	Increase
CS	1.0554%	1.2011%	Increase
SR			
Indices	Pre-reform	Post-reform	Change in Performance
IS1	13.59%	6.65%	Decrease
IS2	16.02%	8.16%	Decrease
IS3	0.69%	−0.38%	Decrease
MS	12.53%	4.86%	Decrease
CS	13.05%	4.90%	Decrease
TR			
Indices	Pre-reform	Post-reform	Change in Performance
IS1	4.22%	2.26%	Decrease
IS2	5.97%	3.49%	Decrease
IS3	0.14%	−0.11%	Decrease
MS	4.63%	2.12%	Decrease
CS	4.90%	2.15%	Decrease
VaR			
Indices	Pre-reform	Post-reform	Change in Performance
IS1	0.6998%	0.7181%	Increase
IS2	0.8635%	0.8549%	Decrease
IS3	0.4581%	0.5689%	Increase
MS	0.8137%	0.8410%	Increase
CS	0.8450%	0.8292%	Decrease
CVaR			
Indices	Pre-reform	Post-reform	Change in Performance
IS1	2.69%	0.06%	Decrease
IS2	3.61%	0.34%	Decrease
IS3	0.40%	1.56%	Increase
MS	2.37%	0.95%	Decrease
CS	2.50%	1.04%	Decrease

Note: SR refers to the stock index Sharpe ratio; TR is the Treynor ratio; VaR is the value at risk; and CVaR is the conditional value at risk.

7.2.2 Second Objective

Did the volatility patterns change for each of the three stock categories in Saudi Arabia following the reforms?

To address this objective, the research employed a range of symmetrical and asymmetrical GARCH frameworks, as well as volatility persistence and half-life techniques, to construct a more comprehensive response. These are described in the following sections.

7.2.2.1 Summary of Univariate Volatility Analysis

This study used a clustering analysis to examine Saudi stock returns in chapter 5. By plotting Saudi stock index prices and returns, the study was able to identify clusters of volatility with similar return patterns. Doing so provided insights into which stocks are likely to move in the same direction and may offer opportunities to diversify investment portfolios. The ARCH-LM test was used to confirm the existence of the ARCH effect, thereby allowing for the use of the GARCH framework for further analysis. By analysing clusters of global markets and the volatility of Saudi stock indices, investors may better understand the overall market and make more informed investment decisions.

The analysis of the univariate GARCH models, namely GARCH (1,1), EGARCH (1,1) and GJR-GARCH (1,1), for the Islamic, mixed and non-Islamic indices' daily returns, as well as the Brent, WTI and S&P 500 indices' external factors, revealed that all the elements of the conditional variance equations significantly affected (predictive power) the volatility of current returns with 1% confidence. The presence of leverage (asymmetrical) effects was also confirmed, with negative shocks predicting higher conditional variance (volatility) than positive shocks. Comparative analyses of the pre- and post-reform periods revealed a slight change in the ARCH effect per the GJR-

GARCH models, as well as a decrease in the asymmetrical power values. These findings suggest a similar conclusion to that by Bensethom (2021) in that liberalising the stock market may reduce the impact of bad news on conditional variance (volatility). The greater transparency and higher numbers of participants (QFIIs) associated with liberalisation can lead to a more efficient stock market and less volatility when bad news is released (Rejeb & Boughrara 2013; Li et al. 2020). Moreover, the log likelihood, the Akaike information criterion and the Schwarz criterion agree on the superiority of the EGARCH (1,1) model over the other symmetric GARCH (1,1) and asymmetric GJR-GARCH (1,1) models when estimating the volatility of Saudi stock indices.

Table 7.2 summarises the results from the volatility persistence and half-life analyses. The table shows that the volatility persistence and half-life values of the Saudi stock indices increased post-reform. These observations are consistent with those of earlier empirical studies (Bouri & Yahchouchi 2014; Neaime 2012). The EGARCH (1,1), GJR-GARCH (1,1) and symmetric GARCH (1,1) results indicate increases in volatility persistence for IS1, IS2, IS3, MS and CS during the post-reform period.

Mixed and conventional stocks tended to have a lower half-life compared to the Islamic stock indices (except for IS1) during the pre-reform period. MS and CS each exhibited a larger half-life than the Islamic stock indices during the post-reform period. This suggests that volatility shocks can have a significant impact on the Saudi stock market, depending on the type of market segmentation; whether it is IFP-conforming or not, higher volatility, persistence and half-life correlate with higher returns. For example, the Islamic stock indices (IS1, IS2 and IS3) had low volatility persistence and half-life compared to the mixed index (MS) and non-Islamic index (CS).

In general, IS3 had a longer persistence time than the other indices in both sub-periods. The financial reforms influenced IS3's persistence time, possibly due to lessened noise traders' activities. The increased persistence observed in the other indices may be related to investors' high expectations of the liberalisation reforms, thus leading to higher trading activities. Investors should consider this when forecasting market volatility. According to Saleem et al. (2021), recent economic activities can affect stock market volatility and persistence. Notably, Islamic stocks have the natural ability to better absorb external shocks because of their limited ownership of QFIIs.

Table 7.2: Summary results of volatility persistence and half-life analysis of Saudi stock indices.

	GARCH (1,1)				
Indices	Pre-reform		Post-reform		Change in Volatility
	VP	HL	VP	HL	Persistence
IS1	0.9263	9.05	0.8825	5.55	Decrease
IS2	0.9671	20.72	0.9795	33.46	Increase
IS3	1.0149	46.87	0.9798	33.97	Decrease
MS	0.9586	16.39	0.982	38.16	Increase
CS	0.9619	17.84	0.9832	40.91	Increase
	EGARCH (1,1)				
Indices	Pre-reform		Post-reform		Change in Volatility
	VP	HL	VP	HL	Persistence
IS1	0.9523	14.18	0.9819	37.95	Increase
IS2	0.9532	14.46	0.9693	22.23	Increase
IS3	0.9739	26.21	0.9695	22.38	Decrease
MS	0.9480	12.98	0.9692	22.16	Increase
CS	0.9509	13.77	0.9698	22.60	Increase
	GJR-GARCH (1,1)				
Indices	Pre-reform		Post-reform		Change in Volatility
	VP	HL	VP	HL	Persistence
IS1	0.8611	4.64	0.9354	10.38	Increase
IS2	0.7957	3.03	0.9686	21.73	Increase
IS3	1.0252	27.85	0.9706	23.23	Decrease
MS	0.9463	12.55	0.9711	23.64	Increase
CS	0.9473	12.79	0.9720	24.41	Increase

Note: VP refers to the volatility persistence estimation; HL is the half-life to die down in days.

7.2.3 Third Objective

Does volatility spillover between the oil market and US stock market returns vary for each of the three Saudi stock index categories pre- and post-reform?

The next section presents the results of the volatility spillover investigation between the selected global markets (Brent, WTI and S&P 500) and five Saudi stock indices. The investigation applied three statistical techniques: ARMA-GARCH (1,1), two-step CCF tests and bivariate VAR-GARCH-BEKK (1,1). The analysis covered the full sample, as well as the pre-reform, post-reform and COVID-19 periods.

7.2.3.1 Summary of Volatility Spillover Investigation

The findings of this study show that the liberalisation of the Saudi stock market has had an overall significant impact on the volatility spillover between the different markets, with the volatility spillover increasing in the post-reform period.

First, the results of the ARMA-GARCH (1,1) estimation support the empirical findings of Grosvenor and Greenidge (2012) and Sun et al. (2023), suggesting that there is statistically significant volatility spillover from global markets (Brent, WTI and S&P 500) to Saudi stock indices both pre- and post-reform. The volatility spillover size increased during the post-reform period, with the Islamic stock indices exhibiting greater growth in volatility spillover from the global markets compared to the mixed and convectional indices (MS and CS). This may indicate that Islamic investments provide investors with more diversification options than do conventional stocks (Sakti et al. 2018). This supports previous studies by Saiti and Masih (2016) and Al-Awadhi et al. (2018), who implied the existence of market segmentation based on the IFP created by the different risk-return patterns of Islamic and non-Islamic stocks. This study suggests that the higher volatility spillover from the global indices may be the result of liberalisation, improved liquidity, reduced regulation complexity, increased transparency and additional disclosure requirements. The ARMA-GARCH (1,1) revealed that the interdependence between the volatility of S&P 500 and the Saudi stock indices is greater than that of the oil market indices (Brent and WTI) and the Saudi stock indices in both the pre- and post-reform periods (Khalifa et al. 2012).

Second, the results of the CCF estimations support previous ARMA-GARCH (1,1) estimation outcomes. They indicate that the variance (volatility) of the Brent return was significant at 5%, thus causing the variance (volatility) of the MS and CS returns more than the Islamic stock indices at lag 0 and lag 1. WTI and S&P 500 return variances caused variances in all the Saudi stock index returns at lag 0 and lag 1, with increased lag and lead values during the financial reforms. The financial reforms were marked by increased volatility in the stock indices, further increasing the correlations between the global markets and Saudi stock indices. The increased variances of the Brent, WTI and S&P 500 returns thus directly impacted the Saudi stock index returns. The results also suggest that the causality in variance between S&P 500 returns to IS1, IS2, IS3, MS and CS exists at lag 0, lag 1 and lag 10 post-reform, except for IS1 at lag 0. Overall, the CCF test results support previous ARMA-GARCH (1,1) estimation outcomes for volatility spillover between the local Saudi stock indices and global markets (Finta et al. 2019).

Third, the study used a bivariate VAR-GARCH-BEKK approach to analyse volatility and cross-volatility spillover between the Saudi stock indices and selected global markets. The overall findings are in line with those by Hammoudeh and Choi (2006), Jouini (2013) and Jouini and Harrathi (2014), who showed that Saudi stock indices react positively to changes in the oil and US stock markets. This indicates that these markets significantly influence the Saudi stock market. However, unlike the ARMA-GARCH (1,1) results, this estimation suggests that the Saudi stock indices' interdependency with the oil market is significantly greater than with S&P 500. Moreover, the Islamic and mixed stock indices correlate to the oil market and to the US stock market more than the non-Islamic index does (Shahzad et al. 2018). This suggests that Islamic stocks can provide better hedging during times of crisis (Hassan et al. 2019). The US stock market was also identified as a major source of information shock and volatility spillover to IS1 post-reform. Ultimately, the findings suggest that investors in the Saudi stock market should closely monitor the oil and US stock markets to better understand the dynamics of their investments.

Bivariate VAR-GARCH-BEKK (1,1) estimations show that the liberalisation of the Saudi stock market has significantly affected the shock and volatility spillover between Saudi stock indices and global markets. The bivariate VAR-GARCH-BEKK estimations show that the Saudi stock indices are more sensitive to external shocks and volatility spillover, particularly from S&P 500 and WTI. These results are consistent with the empirical findings of Korkusuz et al. (2022), who indicated that the volatility spillover from Saudi stock indices to global markets increased significantly post-reform. Volatility spillover between S&P 500 and Saudi stock indices increased during the post-reform period, but was insignificant except for one of the Islamic stock indices (IS1). Table 7.3 and Table 7.4 present the statistically significant shock and volatility spillover between the selected global markets and Saudi stock indices based on the bivariate VAR-GARCH-BEKK estimations. Investors should take this information into account when making investment decisions; they should also consider that WTI significantly impacts the volatility of Saudi stock indices.

Table 7.3: Results summary of shock spillover between global markets and Saudi stock indices, based on the bivariate VAR-GARCH estimations, for the full study period and sub-periods.

		Shock Spillover			
Global Market	Saudi Index	Full Sample	Pre-reform	Post-reform	COVID-19
Brent	IS1	←	↔	↔	/
Brent	IS2	←	↔	→	/
Brent	IS3	/	←	/	/
Brent	MS	↔	↔	→	/
Brent	CS	←	↔	→	/
WTI	IS1	↔	→	←	/
WTI	IS2	↔	↔	/	/
WTI	IS3	→	←	↔	/
WTI	MS	↔	→	→	/
WTI	CS	↔	→	↔	/
S&P 500	IS1	/	/	→	/
S&P 500	IS2	/	/	/	/
S&P 500	IS3	/	/	/	/
S&P 500	MS	/	/	/	/
S&P 500	CS	/	/	/	/

Note: The symbols (→) and (←) indicate the direction of shock spillover from the global market to the Saudi stock indices, and from the Saudi stock indices to the global market, respectively. (↔) indicates significant shock transmission between the global markets and the Saudi stock indices. (/) indicates no significant shock spillover between the two markets.

Table 7.4: Results summary of volatility spillover between the global markets and Saudi stock indices, based on the bivariate VAR-GARCH estimations, for the full study period and sub-periods.

		Volatility Spillover			
Global Market	Saudi Index	Full Sample	Pre-reform	Post-reform	COVID-19
Brent	IS1	↔	↔	/	/
Brent	IS2	↔	→	→	/
Brent	IS3	→	/	/	/
Brent	MS	↔	→	→	/
Brent	CS	↔	→	→	/
WTI	IS1	↔	→	↔	/
WTI	IS2	↔	→	↔	/
WTI	IS3	→	/	↔	/
WTI	MS	↔	→	↔	/
WTI	CS	↔	→	↔	/
S&P 500	IS1	/	/	↔	/
S&P 500	IS2	/	/	/	/
S&P 500	IS3	/	/	/	/
S&P 500	MS	/	/	/	/
S&P 500	CS	/	/	/	/

Note: The symbols (→) and (←) indicate the direction of volatility spillover from the global market to the Saudi stock indices, and from the Saudi stock indices to the global market, respectively. (↔) indicates significant volatility transmission between both global markets and the Saudi stock indices. (/) indicates no significant volatility spillover between the two markets.

7.2.4 Fourth Objective

Does the selection of optimal portfolios vary among the three stock categories (based on Islamic principles) pre- and post- financial reform?

To identify the implications of volatility spillover on portfolio selection, this section presents the summary results of the optimal portfolio weights by Kroner and Ng (1998) and hedge ratio estimation by Kroner and Sultan (1993), with a comparison of the stock index categories based on IFP.

7.2.4.1 Summary of Portfolio Management Implications

As shown in Table 7.5, the overall results from the optimal portfolio weights and hedge ratios for the Saudi and global portfolios suggest that investors should invest more in Saudi stocks than in oil. These overall findings are consistent with those by Hammoudeh and Choi (2006), Jouini (2013) and Jouini and Harrathi (2014), who found that Saudi stocks have more weight in oil/Saudi stock portfolios. Our overall results recommend holding fewer Saudi assets in a Saudi/S&P 500 portfolio to reduce risk without decreasing expected returns. The highest portfolio weighting for Saudi assets was found in the Saudi stock/Brent portfolios, while the lowest portfolio weights for Saudi assets was found in a Saudi/S&P 500 portfolio. The pre-reform and post-reform periods both saw increases in the optimal weight for Saudi assets in Saudi stock/Brent portfolios and an increase in hedge ratios post-reform. The WTI/Saudi stock hedge ratio results were mixed, while the S&P 500/Saudi stock hedge ratios revealed difference between the Islamic stock indices, mixed stock index and non-Islamic stock index. Investors may want to consider a short strategy with Islamic stock portfolios more than with their conventional counterparts. The findings also indicate that the Islamic stock index was less affected by the post-reform period compared to the other indices (Hassan et al. 2019).

Table 7.5: Summary results of optimal weight and hedge ratio analyses of global and Saudi stock portfolios.

Portfolio	Pre-reform		Post-reform		Change in Portfolio
Brent					
	W	β	W	β	
Brent/IS1	0.20	0.13	0.13	0.68	Decrease Brent
Brent/IS2	0.21	0.14	0.11	0.46	Decrease Brent
Brent/IS3	0.12	0.33	0.13	0.35	No major change
Brent/MS	0.22	0.22	0.13	0.45	Decrease Brent
Brent/CS	0.19	0.24	0.13	0.60	Decrease Brent
WTI					
Portfolio	Pre-reform		Post-reform		Change in Portfolio
	W	β	W	β	
WTI/IS1	0.24	0.12	0.15	0.33	Decrease WTI
WTI/IS2	0.25	0.14	0.12	0.44	Decrease WTI
WTI/IS3	0.14	0.28	0.15	0.39	No major change
WTI/MS	0.25	0.14	0.12	0.44	Decrease WTI
WTI/CS	0.25	0.13	0.15	0.35	Decrease WTI
S&P 500					
Portfolio	Pre-reform		Post-reform		Change in Portfolio
	W	β	W	β	
S&P 500/IS1	0.47	0.20	0.65	0.20	Increase S&P 500
S&P 500/IS2	0.00	1.33	0.61	0.23	Increase S&P 500
S&P 500/IS3	0.30	0.44	0.63	0.21	Increase S&P 500
S&P 500/MS	0.47	0.19	0.63	0.23	Increase S&P 500
S&P 500/CS	0.49	0.21	0.65	0.22	Increase S&P 500

Note: W refers to the optimal portfolio weight and β is the hedge ratio of the Global/Saudi stock portfolio.

7.3 Policy Implications

The findings of this thesis have substantial in-depth consequences for comprehending the return and volatility behaviours of the Saudi stock market within the context of Islamic financial principles (social norms). The findings are expected to help policymakers and Saudi stock market investors as follows:

1. Portfolio managers can develop strategies for mitigating risk during periods of high volatility by paying attention to stock market segmentations based on IFP. By analysing the performance of different segments of the stock market and identifying those less susceptible to volatility, managers can better diversify their portfolios to reduce the potential risk associated with an unpredictable market.

Additionally, they can use IFP to identify which stocks are expected to perform better during periods of increased volatility and thereby benefit from market movements. By implementing such strategies, portfolio managers can better manage their risk exposure and maximise returns during times of high volatility.

2. Investment and portfolio managers should pay close attention to time-varying volatility across markets and adjust their strategies accordingly. This is especially important in light of the Saudi Public Investment Fund’s decision to increase global market assets and decrease equity in the Saudi stock market. To maximise opportunities for success, portfolio managers should continually analyse changing market conditions and adjust their strategies to optimise their portfolios. Policymakers should consider the implications of this shift in the Saudi Public Investment Fund’s strategy when developing policies to ensure a stable and prosperous financial sector.

3. The CMA should consider further liberalisation measures, particularly in times of economic crisis. An effective strategy to mitigate risk during times of high volatility is to target the QFIIs by promoting IFP-confirming stocks. Such will open opportunities for investors and could help stabilise the Saudi stock market. Additional initiatives could be introduced to further liberalise the market, such as enabling foreign investors to access new investments, extending the range of tradable products and reducing the cost of trading. Such measures could help ensure that the markets remain accessible and efficient for all investors.

4. To effectively develop policy implications for stock market research in Saudi Arabia, researchers and analysts should consider incorporating more structural break analyses into their empirical analyses. This would enable them to better

understand the changes in the Saudi stock market over time and help identify potential changes that could impact the development of policy implications.

5. The stakeholders in the Saudi stock market or any Islamic countries such as investors, policy makers, analysts, researchers, and global stock indices providers must consider the effects on Islamic principles as it affect the individuals and institutions social norms. According to Rajput et al. (2023) it is informative to understand the volatility pattern of Islamic stock markets taking into account the risk of geopolitical factor towards policy formulation. This would be helpful in determining the level of liberalisation in the market, assets prices, trading plans, investment hedging and policy regulations.

Moreover, the findings of this thesis have significant implications for understanding the financial reforms (liberalization) of the Saudi stock market. In line with these efforts, Saudi Arabia became a participant in the Sustainable Stock Exchanges (SSE) initiative, established by the United Nations (UN) in late 2018. The SSE aims to facilitate the advancement of several of the 17 Sustainable Development Goals (SDGs) adopted by the UN through stock markets across 133 countries.[29] According to the Department of Economic and Social Affairs (2023), the SSE initiative prioritizes five SDG targets that are highly relevant to this thesis:

1. SDG 5: Gender Equality: This goal strives to address gender disparities in participation within and among countries. The modernization of the Saudi stock market can play a significant role in creating a more inclusive financial system, fostering broader participation, and reducing gender inequalities. Achieving gender equality within the stock market involves promoting female representation

[29] 133 stock markets have joined to the SSE by the year of 2023.

in leadership and decision-making positions, ensuring equal access to capital and investment opportunities for women, enhancing corporate governance practices to encourage gender diversity, and incorporating gender considerations in socially responsible investing (ESG) strategies. By embracing these aspects, the Saudi stock market can contribute to advancing gender equality and empowering women in the financial sector.

2. SDG 8: Decent Work and Economic Growth: This goal underscores the importance of promoting sustained, inclusive, and sustainable economic growth, along with providing full and productive employment opportunities and decent work for all. The development of the Saudi stock market can significantly contribute to improving economic growth and generating more job opportunities. Enhancing the technological infrastructure and regulatory framework of the stock market aligns with this goal, as it fosters an environment conducive to economic expansion, facilitates access to capital for businesses, and promotes a robust and fair financial ecosystem. By advancing these aspects, the Saudi stock market can contribute to promoting decent work and supporting economic growth and prosperity for all.

3. SDG 12: Responsible Consumption and Production: This goal urges companies, particularly large and transnational ones, to embrace sustainable practices and incorporate sustainability information into their reporting processes. In the context of the Saudi stock market, policymakers can enhance various aspects, including transparency, corporate governance, and environmental disclosure requirements. By strengthening these areas, the stock market can encourage sustainable investment choices and foster responsible business practices.

Promoting transparency allows investors to make informed decisions, corporate governance practices ensure accountability and ethical conduct, and environmental disclosure requirements push companies towards sustainable production and consumption patterns. These actions align with SDG 12 and contribute to more sustainable and responsible stock market ecosystem.

4. SDG 13: Climate Action: This goal calls for urgent action to combat climate change and its consequences. It encompasses enhancing education, awareness, and the capacity of individuals and institutions in climate change mitigation, adaptation, impact reduction, and early warning systems. Saudi Arabia's ambitious initiatives to reduce carbon emissions through innovations, the diversification of energy sources (including green energy), and the implementation of regional initiatives not only contribute to mitigating climate change but also raise awareness about the global warming issue. By demonstrating commitment to climate action, Saudi Arabia's efforts align with SDG 13 and contribute to addressing the challenges posed by climate change and fostering a more sustainable future.

5. SDG 17: Partnerships for the Goals: This goal emphasizes the significance of fostering global partnerships to achieve sustainable development. Saudi Arabia's active participation and collaboration with international financial institutions, investors, and market participants can effectively support the ongoing modernisation efforts and align them with global sustainability objectives. The country's strength lies in its active engagement with these diverse institutions. Therefore, it is recommended to continue fostering and strengthening these global partnerships. By doing so, Saudi Arabia can leverage collective expertise,

resources, and knowledge-sharing to drive the modernization of its stock market and advance sustainable development, thereby contributing to the achievement of SDG 17 and the broader global sustainability agenda.

7.4 Limitations and Recommendations for Further Research

Time, financial and physical obstacles may have limited the potential of this study. However, the analysis still offers a unique look into the volatility behaviours of the Saudi stock market, Islamic stock markets and the MENA region.

This study was limited to the period between 04 January 2010 and 29 June 2021, and it only covered the Saudi stock market, the oil market (Brent and WTI) and the US stock market (S&P 500). The analysis did not consider any other regional or global stock markets. Furthermore, the analysis only examined the performance of the Saudi stock market and how its volatility reacts to three global markets; it did not consider other factors, such as economic or geopolitical developments. As such, the findings of this study may not apply to other markets or regions.

This study did not consider the impact of any external factors, such as currency rate changes, geopolitical developments or other factors that could affect stock market performance. Additionally, the study did not consider such factors as the macroeconomic environment of the country or the impact of government policies on the stock market.

Further research should explore the volatility behaviours of the Saudi stock market, as well as other Islamic and non-Islamic societies with IFP-confirming assets, in greater depth. Expanding the study period to include more recent events and policies, such as the 2022 Russia and Ukraine war, could provide additional empirical evidence on volatility pattern reactions. Research might also focus on the spillover effects of different asset classes, such as stocks, commodities, bonds and currencies, in different countries. It would be interesting to examine the existence, direction and size of the spillover effect between different market segments based on the Islamic principles in the same market. It would also be beneficial to compare the Saudi stock market to other countries inside and outside the GCC region, such as China, which is Saudi Arabia's first trade partner. Different statistical tools should also be used to capture the multifaceted impacts of liberalisation and the COVID-19 pandemic. For instance, simple regression could be used to investigate the impact of COVID-19, while more complex GARCH models could be used to analyse the effects of policy changes in larger sample sizes.

In future research, it would be valuable to explore and incorporate alternative unit root tests such as the Narayan and Popp (2010) test. This test allows for the analysis of the combined effects of structural breaks and time trends, although it does not explicitly account for heteroscedasticity in the data. Additionally, Narayan and Liu (2015) test, which is a GARCH-based unit root test, could be another alternative to consider. This test incorporates both structural breaks and heteroscedasticity, but does not model time trends (Salisu et al. 2021). By integrating both the Narayan and Popp (2010) test and the Narayan and Liu (2015) test in future GARCH studies, a more comprehensive approach can be achieved. This approach would provide a robust framework for analysing financial time series data, capturing the combined effects of structural breaks, time trends, and heteroscedasticity. This integrated methodology has the potential to enhance the estimation and understanding of volatility dynamics in financial markets. The incorporation of these alternative unit root tests in future research will contribute to a more thorough examination of the stationarity properties of time series data, enabling a deeper analysis of the underlying processes and dynamics. It is an exciting avenue to explore and can lead to more accurate modelling and forecasting of volatility in financial markets.

REFERENCES LIST

Abdalla, SZS 2012, ‘The risk-return trade-off in emerging stock markets: Evidence from Saudi Arabia and Egypt’, *International Journal of Economics and Finance*, vol. 4, no. 6, pp. 216-229.

Abraham, A, Seyyed, FJ and Al-Elg, A 2001, ‘Analysis of diversification benefits of investing in the emerging gulf equity markets’, *Managerial Finance*, vol. 27, no. 10-11, pp. 47-57.

Abu Hasan, M 2017, ‘Efficiency and volatility of the stock market in Bangladesh: A macroeconometric analysis’, *Turkish Economic Review*, vol. 4, no. 2, pp. 239-249.

Abuzayed, B and Al-Fayoumi, N 2017, ‘Are investors concerned with stock market upgrades? Evidence from multivariate framework analysis’, *Emerging Markets Finance and Trade*, vol. 53, no. 10, pp. 2242-2258.

Ackert, L, and Smith, B 1993, ‘Stock price volatility, ordinary dividends, and other cash flows to shareholders’, *Journal of Finance,* vol. 48, no. 4, pp. 1147-1160.

Adam, K, Marcet, A, and Nicolini, J 2016, ‘Stock market volatility and learning’, *The Journal of Finance*, vol. 71, no. 1, pp. 33-82.

Adams, S and Opoku, E 2015, ‘Foreign direct investment, regulations and growth in sub-Saharan Africa’, *Economic Analysis and Policy*, vol. 47, pp. 48-56.

Adesi, GB 2016, 'VaR and CVaR Implied in Option Prices', *Journal of Risk and Financial Management*, vol. 9, no. 1, viewed 18 September 2021, https://doi.org/10.3390/jrfm9010002.

Agénor, PR 2001, ‘Benefits and costs of international financial integration: theory and facts’, *Policy Research Working Paper No. 2788, The World Bank Group.*

Ahmed, A and Huo, R 2018, ‘China–Africa financial markets linkages: Volatility and Interdependence’, *Journal of Policy Modeling*, vol. 40, no. 6, pp.1140-1164.

Ahmed, A and Mmolainyane, K 2014, ‘Financial integration, capital market development and economic performance: Empirical evidence from Botswana’, *Economic Modelling*, vol. 42, pp. 1-14.

Ahmed, RR, Vveinhardt, J, Streimikiene, D and Channar, ZA 2018, ‘Mean reversion in international markets: evidence from G.A.R.C.H. and half-life volatility models’, *Economic Research-Ekonomska Istraživanja*, vol. 31, no.1, pp. 1198-1217.

Ahmed, WM 2019, ‘Islamic and conventional equity markets: Two sides of the same coin, or not?’, *The Quarterly Review of Economics and Finance*, vol. 72, pp. 191-205.

Aityan, S, Ivanov-Schitz, A and Izotov, S 2010, ‘Time-shift asymmetric correlation analysis of global stock markets’, *Journal of International Financial Markets, Institutions & Money*, vol. 20, no. 5, pp. 590-605.

Al Awadhi, A and Dempsey, M 2017, ‘Social norms and market outcomes: The effects of religious beliefs on stock markets’, *Journal of International Financial Markets, Institutions and Money*, vol. 50, pp. 119-134.

Al Nasser, O and Hajilee, M 2016, ‘Integration of emerging stock markets with global stock markets’, *Research in International Business and Finance*, vol. 36, pp. 1-12.

Al-Awadhi, A, Al-Saifi, K, Al-Awadhi, A, Alhamadi, S 2020, ‘Death and contagious infectious diseases: impact of the COVID-19 virus on stock market returns’, *Journal of Behavioral and Experimental Finance*, vol. 27, p. 100326

Al-Awadhi, A, Dempsey, M, and Marisetty, V 2016, ‘Social norms and market segmentation: The effects of religious beliefs on stock market returns, liquidity, and liquidity risk', Paper presented to KFUPM Islamic Banking and Finance Research Conference, Riyadh, 14-15 March 2016.

Al-Najjar, DM 2016, 'Modelling and estimation of volatility using ARCH/GARCH models in Jordan's stock market', *Asian Journal of Finance & Accounting*, vol. 8, no. 1, pp. 152-167.

Alam, MM, Akbar, CS, Shahriar, SM and Elahi, MM 2017, 'The Islamic shariah principles for investment in Stock Market', *Qualitative Research in Financial Markets*, vol. 9, no. 2, pp. 132-146.

Albahooth, B and Kulendran, N 2020, 'The interdependence of oil prices affecting the stock market performance: A sectoral analysis of GCC stock markets', *Australian Academy of Accounting and Finance Review*, vol. 5, no. 1, pp. 1-12.

Albassam, B 2015, 'Economic diversification in Saudi Arabia: myth or reality?', *Resources Policy*, vol. 44, pp. 112-117.

Alghfais, M 2018, 'Forecasting the saily stock market volatility of the TASI Index: An ARCH family models approach', *SAMA Working Paper No. WP/18/1, Saudi Central Bank.*

Alhomaidi, A, Hassan, M, Hippler, W, and Mamun, A 2019, 'The impact of religious certification on market segmentation and investor recognition', *Journal of Corporate Finance*, vol. 55, pp. 28-48.

Ali, G 2013, 'EGARCH, GJR-GARCH, TGARCH, AVGARCH, NGARCH, IGARCH and APARCH models for pathogens at marine recreational sites', *Journal of Statistical and Econometric Methods*, vol. 2, no. 3, pp. 57-73.

Ali, MA, Aqil, M, Alam Kazmi, SH, and Zaman, SI 2021, 'Evaluation of risk adjusted performance of mutual funds in an emerging market', *International Journal of Finance & Economics.*

Alikhanov, A 2013, ‘To what extent are stock returns driven by mean and volatility spillover effects? – Evidence from eight European stock markets’, *Review of Economic Perspectives,* vol. 13, no.1, pp. 3-29.

Aliyev, F, Ajayi, R and Gasim, N 2020, 'Modelling asymmetric market volatility with univariate GARCH models: Evidence from Nasdaq-100', *The Journal of Economic Asymmetries,* vol. 22, article no. e00167, viewed 20 July 2021, https://doi.org/10.1016/j.jeca.2020.e00167.

Almohaimeed, A and Harrathi, N 2013, ‘Volatility transmission and conditional correlation between oil prices, stock market and sector indexes: Empirics for Saudi stock market’, *Journal of Applied Finance & Banking*, vol. 3, no. 4, pp. 125-141.

Alotaibi, A, and Mishra, A 2014, ‘Determinants of international financial integration of GCC markets’, In Arouri, M, Boubaker, S, and Nguyen, D (Eds), *Emerging Markets and the Global Economy,* pp. 749-771.

Alotaibi, K, Helliar, C, and Tantisantiwong, N 2020, ‘Competing logics in the Islamic funds industry: A market logic versus a religious logic’, *Journal of Business Ethics,* vol. 175, pp. 207–230

Alqadhib, H, Kulendran, N, and Seelanatha, L 2022, ‘Impact of COVID-19 on mutual fund performance in Saudi Arabia’, *Cogent Economics & Finance*, vol. 10, no. 1, Article no. 2056361., viewed 14 December 2022, https://doi.org/10.1080/23322039.2022.2056361.

Alqahtani, A, Lahiani, A, and Salem, A 2020, ‘Crude oil and GCC stock markets: New evidence from GARCH co-integration and Granger causality approaches’, *International Journal of Energy Sector Management*, vol. 14, no. 4, pp. 745-756.

Alrobian, A(2020). Saudi financial market: Establishment, performance, and efficiency. Riyadh, KSA: PMI.

Alsharif, M 2020, 'The Relationship between the Returns and Volatility of Stock and Oil Markets in the Last Two Decades: Evidence from Saudi Arabia', *International Journal of Economics and Financial Issues*, vol. 10, no. 4, pp. 1-8.

Amaya, D, Christoffersen, P, Jacobs, K and Vasquez, A 2015, 'Does realized skewness predict the cross-section of equity returns?', *Journal of Financial Economics*, vol. 118, no. 1, pp. 135-167.

Antonakakis, N, Floros, C and Kizys, R 2016, 'Dynamic spillover effects in futures markets: UK and US evidence', *International Review of Financial Analysis*, vol. 48, pp. 406-418.

Antoniou, A, and Holmes, P 1995, 'Futures trading, information and spot price volatility: Evidence for the FTSE-100 stock index futures contract using GARCH', *Journal of Banking & Finance*, vol. 19, no. 1, pp. 117-129.

Antoniou, A, Holmes, P and Priestley, R 1998, 'The effects of stock index futures trading on stock index volatility: An analysis of the asymmetric response of volatility to news', *The Journal of Futures Markets*, vol. 18, no. 2, pp. 151-166.

Aouadi, A, Arouri, M and Teulon, F 2015, 'Investor Following and Volatility: A GARCH Approach', *Journal of Applied Business Research (JABR*), vol. 31, no. 3, pp. 765-780.

Apergis, N, and Miller, SM 2009, 'Do structural oil-market shocks affect stock prices?', *Energy Economics*, vol. 31, no. 4, pp. 569-575.

Arouri, M, Lahiani, A and Nguyen, D 2011, 'Return and volatility transmission between world oil prices and stock markets of the GCC countries', *Economic Modelling*, vol. 28, no. 4, pp.1815-1825.

Arouri, MEH and Rault, C 2010, ‘Causal relationships between oil and stock prices: Some new evidence from gulf oil-exporting countries’, *Economie internationale*, vol. 2, pp. 41-56.

Arshad, S, Rizvi, S, Ghani, G, and Duasa, J 2016, ‘Investigating stock market efficiency: A look at OIC member countries’, *Research in International Business and Finance*, vol. 36, pp. 402-413.

Ashfaq, S, Yong, T, and Rashid, M 2019, ‘Volatility spillover impact of world oil prices on leading Asian energy exporting and importing economies stock returns’, *Energy,* vol. 188, article no. 116002, viewed 10 May 2021, https://doi.org/10.1016/j.energy.2019.116002.

Awartani, B, Maghyereh, A, and Al Shiab, M 2013, ‘Directional spillovers from the US and the Saudi market to equities in the Gulf Cooperation Council countries’ *Journal of International Financial Markets, Institutions and Money*, vol. 27, pp. 224-242.

Babu, A, and Paul, S 2014, ‘Volatility spillover between oil and stock market returns’, *Indian Economic Review*, vol. 49, no. 1, pp. 37-56.

Bagchi, B 2017, ‘Volatility spillovers between crude oil price and stock markets: evidence from BRIC countries’, *International Journal of Emerging Markets*, vol. 12, no. 2, pp. 352-365.

Baker, H and Nofsinger, J 2012, *Socially responsible finance and investing: Financial institutions, corporations, investors, and activists*. Hoboken, NJ: John Wiley & Sons.

Baker, S, Bloom, N, and Davis, S 2016, ‘Measuring economic policy uncertainty’, *The Quarterly Journal of Economics*, vol. 131, no. 4, pp. 1593-1636.

Balakrishnan, K, Vashishtha, R, and Verrecchia, R, 2019, 'Foreign competition for shares and the pricing of information asymmetry: Evidence from equity market liberalization', *Journal of Accounting and Economics*, vol. 67, no. 1, pp. 80-97.

Balcilar, M, Demirer, R and Hammoudeh, S 2015, 'Regional and global spillovers and diversification opportunities in the GCC equity sectors', *Emerging Markets Review*, vol. 24, pp. 160-187.

Balli, F, Basher, SA and Louis, RJ 2013, 'Sectoral equity returns and portfolio diversification opportunities across the GCC region', *Journal of International Financial Markets, Institutions and Money,* vol. 25, pp. 33-48.

Banani, A and Hidayatun, NA 2017, 'Performance of Islamic indices: risk adjusted returns of sharia compliant stocks on Jakarta Islamic index and Dow jones Islamic turkey', *Journal of Economics & Business,* vol. 1, no. 1, pp. 1-18.

Bandi, FM and Renò, R 2012, 'Time-varying leverage effects', *Journal of Econometrics*, vol. 169, no. 1, pp. 94-113.

Banumathy, K and Azhagaiah, R 2015, 'Modelling stock market volatility: Evidence from India', *Managing Global Transitions: International Research Journal*, vol. 13, no. 2, pp. 27-41.

Batuo, M, Mlambo, K, and Asongu, S 2018, 'Linkages between financial development, financial instability, financial liberalisation and economic growth in Africa', *Research in International Business and Finance*, vol. 45, pp. 168-179.

Bauwens, L, Lauren, S, Rombouts, JVK 2006, 'Multivariate GARCH models: a survey', *Journal of Applied Econometrics,* vol. 21, pp. 79-109.

Bayraci, Selcuk 2007, '*Modeling the volatility of FTSE All Share Index Returns',* MPRA artical no. 28095, viewed 12 May 2021, https://mpra.ub.uni-muenchen.de/id/eprint/28095

Beine, M, Cosma, A and Vermeulen, R 2010, ‘The dark side of global integration: Increasing tail dependence’, *Journal of Banking & Finance,* vol. 34, no. 1, pp. 184-192.

Bekaert, G and Wu, G 2000, ‘Asymmetric volatility and risk in equity markets’, *The Review of Financial Studies*, vol. 13, no. 1, pp. 1-42.

Bekaert, G, Ehrmann, M, Fratzscher, M, and Mehl, A 2014, ‘The global crisis and equity market contagion’, *The Journal of Finance*, vol. 69, no. 6, pp. 2597-2649.

Bekaert, G, Harvey, C, and Lundblad, C 2011, ‘Financial openness and productivity’, *World Development*, vol. 39, no. 1, pp. 1-19.

Ben Slimane, F, Mehanaoui, M, and Kazi, I 2013, ‘How does the financial crisis affect volatility behavior and transmission among European stock markets?’, *International Journal of Financial Studies,* vol. 1, no. 3, pp. 81-101.

Bentes, SR 2014, ‘Measuring persistence in stock market volatility using the FIGARCH approach’, *Physica A: Statistical Mechanics and its Applications*, vol. 408, pp.190-197.

Bentes, SR, Menezes, R and Mendes, DA 2008, ‘Long memory and volatility clustering: Is the empirical evidence consistent across stock markets?’, *Physica A: Statistical Mechanics and its Applications*, vol. 387, no. 15, pp. 3826-3830.

Berger, D, Pukthuanthong, K and Yang, JJ 2013, ‘Is the diversification benefit of frontier markets realizable by mean-variance investors? The evidence of investable funds’, *The Journal of Portfolio Management*, vol. 39, no. 4, pp. 36-48.

Bhowmik, R, and Wang, S 2020, ‘Stock market volatility and return analysis: A systematic literature review, *Entropy*, vol. 22, no. 5, article no. 522, viewed 15 May 2023, https://doi.org/10.3390/e22050522

Billmeier, A and Massa, I 2009, 'What drives stock market development in emerging markets-institutions, remittances, or natural resources?' *Emerging Markets Review*, vol. 10, no. 1, pp. 23-35.

Bissoondoyal-Bheenick, E, Brooks, R, Chi, W, and Do, H 2018, 'Volatility spillover between the US, Chinese and Australian stock markets', *Australian Journal of Management*, vol. 43, no. 2, pp. 263-285.

Bodie, Z, Kane, A, and Marcus, AJ 2010, *Investments and portfolio management (9th ed.)*. New York: McGraw-Hill/Irwin.

Bollerslev, T 1986, 'Generalized autoregressive conditional heteroskedasticity', *Journal of Econometrics*, vol. 31, no. 3, pp. 307-327.

Bollerslev, T 1990, 'Modelling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH model', *Review of Economics and Statistics*, vol. 72, no. 3, pp. 498-505.

Bollerslev, T, Chou, RY, and Kroner, KF 1992, 'ARCH modeling in finance: A review of the theory and empirical evidence', *Journal of Econometrics*, vol. 52, no. 1-2, pp. 5-59.

Booth, G, Martikainen, T, and Tse, Y 1997, 'Price and volatility spillovers in Scandinavian stock markets', *Journal of Banking and Finance*, vol. 21, no. 6, pp. 811-823.

Borgers, A, Derwall, J, Koedijk, K, and Horst, J 2015, 'Do social factors influence investment behavior and performance? Evidence from mutual fund holdings', *Journal of Banking & Finance*, vol. 60, pp. 112-126.

Boussama, F, Fuchs, F, and Stelzer, R 2011, 'Stationarity and geometric ergodicity of BEKK multivariate GARCH models', *Stochastic Processes and Their Applications*, vol. 121, no. 10, pp. 2331-2360.

Brooks, C 2019, *Introductory econometrics for finance (4th ed.)*, Cambridge University Press, Cambridge, UK.

Brooks, C, Burke, S, Persand, G 2003, 'Multivariate GARCH Models: Software choice and estimation issues', *Journal of Applied Econometrics*, vol. 18, no. 6, pp. 725-773.

Burnham, T, Gakidis, H, and Wurgler, J 2018, 'Investing in the presence of massive flows: The case of MSCI country reclassifications', *Financial Analysts Journal*, vol. 74, no. 1, pp. 77-87.

Cable, V 1995, 'The diminished nation-state: A study in the loss of economic power', *Daedalus*, vol. 124, no. 2, pp. 23-53.

Caporale G, Pittis, N, Spagnolo, N 2002, 'Testing for causality-in-variance: An application to the East Asian markets', *International Journal of Finance and Economics, vol.* 7, no. 3, pp. 235-245.

Caporale, G, and Spagnolo, N 2012, 'Stock market integration between three CEECs', *Journal of Economic Integration*, vol. 27, no.1, pp. 115-122.

Cevik, E, Dibooglu, S, Abdallah, A, and Al-Eisa, E 2021, 'Oil prices, stock market returns, and volatility spillovers: Evidence from Saudi Arabia', *International Economics and Economic Policy*, vol. 18, no, 1, pp. 157-175.

Chaudhary, R, Bakhshi, P and Gupta, H 2020, 'Volatility in international stock markets: An empirical study during COVID-19', *Journal of Risk and Financial Management*, vol. 13, no. 9, article no. 208, viewed 16 May 2021, https://doi.org/10.3390/jrfm13090208.

Chaves, D. B., and Viswanathan, V. 2016, 'Momentum and mean-reversion in commodity spot and futures markets', *Journal of Commodity Markets*, vol. 3, no. 1, pp. 39-53.

Chazi, A, Samet, A, and Azad, A 2023, 'Volatility and correlation of Islamic and conventional indices during crises', *Global Finance Journal*, vol. 55, article no. 100800, viewed 16 Jan 2023, https://doi.org/10.1016/j.gfj.2022.100800.

Chen, JH and Huang, CY 2010, 'An analysis of the spillover effects of exchange-traded funds', *Applied Economics*, vol. 42, no. 9, pp. 1155-1168.

Chen, N, Roll, R, and Ross, S 1986, 'Economic forces and the stock market', *Journal of Business*, vol. 59, no. 3, pp. 383-403.

Chen, X and Ghysels, E 2011, 'News—good or bad—and its impact on volatility predictions over multiple horizons', *The Review of Financial Studies*, vol. 24, no. 1, pp. 46-81.

Chen, Z, Du, J, Li, D, and Ouyang, R 2013, 'Does foreign institutional ownership increase return volatility? Evidence from China', *Journal of Banking & Finance*, vol. 37, no. 2, pp. 660-669.

Cheung, Y and Ng, L1996, 'A causality-in-variance test and its application to financial market prices', *Journal of Econometrics*, vol. 72, no. 1-2, pp. 33-48.

Chi, Z, Dong, F and Wong, HY 2016, 'Option pricing with threshold mean reversion', *Journal of Futures Markets*, vol. 37, no. 2, pp. 107-131.

Chiang, MC, Tsai, IC, and Lee, CF 2011, 'Fundamental indicators, bubbles in stock returns and investor sentiment', *The Quarterly review of Economics and finance*, vol. 51, no. 1, pp. 82-87.

Chou, RY 1988, 'Volatility persistence and stock valuations: Some empirical evidence using GARCH', *Journal of Applied Econometrics*, vol. 3, no. 4, pp. 279-294.

Chu, J, Chan, S, Nadarajah, S and Osterrieder, J 2017, 'GARCH modelling of cryptocurrencies', *Journal of Risk and Financial Management*, vol. 10, no. 4. pp. 17-32.

Chuang, I, Lu, J and Tswei, K 2007, ‘Interdependence of international equity variances: Evidence from East Asian markets’, *Emerging Markets Review*, vol. 8, no. 4, pp. 311-327.

Chun, D, Cho, H and Ryu, D 2019, ‘Forecasting the KOSPI200 spot volatility using various volatility measures’, *Physica A: Statistical Mechanics and its Applications*, vol. 514, pp. 156-166.

Cleveland, C 2009, *Concise encyclopedia of the history of energy*. Cambridge, MA: Academic Press.

Coffie, W 2015, ‘Measuring volatility persistence and risk in Southern and East African stock markets’, *International Journal of Economics and Business Research*, vol. 9, no. 1, pp. 23-36.

Constantinides, GM and Malliaris, AG 1995, ‘Portfolio theory’, *Handbooks in Operations Research and Management Science*, vol. 9, pp. 1-30.

Cont, R 2005, ‘Long range dependence in financial markets’, In Lévy-Véhel, J., Lutton, E. (eds), *Fractals in Engineering*, Springer, London, pp. 159-179.

Cornes, R and Sandler, T 1986, *The theory of externalities, public goods, and club goods*. Cambridge: Cambridge University Press.

Creswell, J 2009, *Research design: Qualitative, quantitative and mixed methods approaches*, Thousand Oaks, CA.

Daly, K 1999, *Financial volatility and real economic activity*, 1st Ed, Ashgate,

Daly, K 2008, ‘Financial volatility: Issues and measuring techniques’, *Physica A: Statistical Mechanics and its Applications*, vol. 387, no. 11, pp. 2377-2393.

Danielsson, J, Valenzuela, M, and Zer, I 2018, ‘Learning from history: Volatility and financial crises’, *The Review of Financial Studies*, vol. 31, no. 7, pp. 2774-2805.

Danyah Alsharif, Shabbir Ahmad. Performance Evaluation: Islamic Mutual Funds Vs. Conventional Mutual Funds in Saudi Arabia--Palarch's Journal Of ArchaeologyOf Egypt/Egyptology 18 (13), 899-909. ISSN1567-214x

Das, S, and Uppal, R 2004, 'Systemic risk and international portfolio choice', *The Journal of Finance*, vol. 59, no. 6, pp. 2451-3006.

De Bondt, WF and Thaler, R 1985, 'Does the stock market overreact?', *The Journal of finance*, vol. 40, no. 3, pp. 793-805.

Debasish, SS 2009, 'Effect of futures trading on spot-price volatility: evidence for NSE Nifty using GARCH', *The Journal of Risk Finance*, vol. 10, no. 1, pp. 67-77.

Dedi, L and Yavas, BF 2016, 'Return and volatility spillovers in equity markets: An investigation using various GARCH methodologies', *Cogent Economics & Finance*, vol. 4, no. 1, article no. 1266788, viewed 17 June 2021, http://dx.doi.org/10.1080/23322039.2016.1266788.

Department of Economic and Social Affairs 2023, *Department of economic and social affairs website*, The United Nation, accessed 22 May 2023, <https://www.sdgs.un.org/>.

Dickey, D, and Fuller, W 1979, 'Distribution of the estimators for autoregressive time series with a unit root', *Journal of the American Statistical Association*, vol. 74, No. 366, pp. 427-431.

Diebold, F and Yilmaz, K 2009, 'Measuring financial asset return and volatility spillovers, with application to global equity markets', *The Economic Journal*, vol. 119, no. 534, pp.158-171.

Diebold, F and Yilmaz, K 2012, 'Better to give than to receive: Predictive directional measurement of volatility spillovers', *International Journal of Forecasting*, vol. 28, no. 1, pp.57-66.

Diebold, F and Yilmaz, K 2015, 'Trans-Atlantic equity volatility connectedness: U.S. and European financial institutions, 2004–2014', *Journal of Financial Econometrics*, vol. 14, no. 1, p.81-127.

Dyhrberg, AH 2016, 'Bitcoin, gold and the dollar – A GARCH volatility analysis', *Finance Research Letters*, vol. 16, pp. 85-92.

Elton, EJ and Gruber, MJ 1997, 'Modern portfolio theory, 1950 to date.', *Journal of Banking & Finance*, vol, 21, no. 11-12, pp. 1743-1759.

Elyasiani, E and Mansur, I 2017, 'Hedge fund return, volatility asymmetry, and systemic effects: A higher-moment factor-EGARCH model', *Journal of Financial Stability*, vol. 28, No. C, pp.49-65.

Emenogu, NG, Adenomon, MO and Nweze, NO 2020, 'On the volatility of daily stock returns of total Nigeria Plc: Evidence from GARCH models, value-at-risk and backtesting', *Financial Innovation*, vol. 6, no. 1, article no. 18, viewed 6 July 2022, https://doi.org/10.1186/s40854-020-00178-1.

Energy Institute 2018, *Energy insight: The black gold of America and its impact on the world.* London, UK: Energy Institute.

Engle, RF 1982, 'Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation', *Econometrica: Journal of the Econometric Society*, vol. 50, no. 4, pp. 987-1007.

Engle, RF 2002, 'Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models', *Journal of Business & Economic Statistics*, vol. 20, no. 3, pp. 339-350.

Engle, RF 2004, 'Risk and volatility: Econometric models and financial practice', *American Economic Review*, vol. 94, no. 3, pp. 405-420.

Engle, RF and Granger, CWJ 1987, 'Co-integration and error correction: Representation, estimation, and testing', *Econometrica*, vol. 55, no. 5, pp. 251-76.

Engle, RF and Kroner, K 1995, 'Multivariate simultaneous generalized ARCH', *Econometric Theory*, vol. 11, no. 1, pp. 122-150.

Engle, RF and Siriwardane, EN 2018, 'Structural GARCH: The volatility-leverage connection', *The Review of Financial Studies*, vol. 31, no. 2, pp. 449-492.

Engle, RF and Susmel, R 1993, 'Common volatility in international equity markets', *Journal of Business & Economic Statistics*, vol. 11, pp. 167-176.

Engle, RF, Focardi, S, and Fabozzi, F 2012, *ARCH/GARCH models in applied financial econometrics, In: Encyclopedia of Financial Models*, John Wiley & Sons, Hoboken, NJ.

Engle, RF, Gallo, GM and Velucchi, M 2012, 'Volatility spillovers in East Asian financial markets: A Mem-based approach', *The Review of Economics and Statistics*, vol. 94, pp. 222-223

Engle, RF, Ito, T and Lin, W-L 1990, 'Meteor Showers or Heat Waves? Heteroskedastic Intra-Daily Volatility in the Foreign Exchange Market', *Econometrica*, vol. 58, no. 3, pp. 525-542.

Epaphra, M 2017, 'Modeling exchange rate volatility: Application of the GARCH and EGARCH models', *Journal of Mathematical Finance*, vol. 7, no. 1, pp. 121-143.

Erdemlioglu, D, Laurent, S and Neely, C 2012, 'Econometric Modeling of Exchange Rate Volatility and Jumps', *Federal Reserve Bank of St. Louis Working Paper No. 2012-008A*, viewed 19 August 2022, http://dx.doi.org/10.2139/ssrn.2038581.

Erdemlioglu, D, Laurent, S and Neely, CJ 2012, 'Econometric modeling of exchange rate volatility and jumps', *Research Division Federal Reserve Bank Working Paper Series 2012-008A*, Eun, C, and Shim, S 1989, 'International transmission of stock market movements', *The Journal of Financial and Quantitative Analysis,* vol. 24, no. 2, pp. 241.

Europa 2018, *Taxation of the financial sector.* Brussels: European Commission.

Fakhfekh, M, Hachicha, N, Jawadi, F, Selmi, N and Idi Cheffou, A 2016, 'Measuring volatility persistence for conventional and Islamic banks: An FI-EGARCH approach', *Emerging Markets Review,* vol. 27, pp. 84-99.

Fama, EF 1965, 'The behavior of stock-market prices', *The Journal of Business,* vol. 38, no. 1, pp. 34-105.

Fama, EF 1976, 'Efficient capital markets: Reply', *The Journal of Finance,* vol. 31, no. 1, pp. 143-145.

Fama, EF and French, KR 1988, 'Permanent and temporary components of stock prices', *Journal of Political Economy,* vol. 96, no. 2, pp. 246-273.

Farzanegan, MR, Hassan, M, and Badreldin, AM 2020, 'Economic liberalization in Egypt: A way to reduce the shadow economy?', *Journal of Policy Modeling*, vol. 42, no. 2, pp. 307-327.

FCM 2018, *Energy CFDs: A look at UK oil and US oil.* London, UK: FCM.

Fedorova, E, and Pankratov, K 2010, 'Influence of macroeconomic factors on the Russian stock market', *Studies on Russian Economic Development,* vol. 21, no. 2, pp. 165-168.

Finta, MA, Frijns, B and Tourani-Rad, A 2019, 'Volatility spillovers among oil and stock markets in the US and Saudi Arabia', *Applied Economics*, vol. 51, no. 4, pp. 329-345.

FTSE Russell 2018, *Saudi Arabia reclassification*. London, UK: FTSE Russell.

G20 Information Centre 2008, *The group of twenty: A history*. Toronto, Canada: University of Toronto.

Garcia, R and Tsafack, G 2011, 'Dependence structure and extreme co-movements in international equity and bond markets', *Journal of Banking & Finance*, vol. 35, pp. 1954-1970.

Garman, B and Klass, J 1980, 'On the estimation of security price volatilities from historical data', *Journal of Business*, vol. 53, no. 1, pp. 67-78.

Garman, MB and Klass, MJ 1980, 'On the Estimation of Security Price Volatilities from Historical Data', *The Journal of Business*, vol. 53, no. 1, pp. 67-78.

Gherghina, ȘC, Armeanu, DȘ, and Joldeș, CC 2020, 'Stock market reactions to COVID-19 pandemic outbreak: Quantitative evidence from ARDL bounds tests and granger causality analysis' International journal of environmental research and public health, vol. 17, no. 18, article no. 6729, viewed 22 May 2023, https://doi.org/10.3390/ijerph17186729

Girard, E and Sinha, A 2008, 'Risk and return in the next frontier', *Journal of Emerging Market Finance*, vol. 7, no. 1, pp. 43-80.

Gkillas, K, Konstantatos, C, Floros, C and Tsagkanos, A 2021, 'Realized volatility spillovers between US spot and futures during ECB news: Evidence from the European sovereign debt crisis', *International Review of Financial Analysis*, vol. 74, article no. 101706, viewed 16 October 2022, https://doi.org/10.1016/j.irfa.2021.101706.

Glosten, L, Jagannathan, R, and Runkle, D 1993, 'On the relation between the expected value and the volatility of the nominal excess return on stocks', *Journal of Finance*, vol. 48, no. 5, pp. 1779-1801.

Goldstein, I, Koijen, RSJ and Mueller, HM 2021, 'COVID-19 and its impact on financial markets and the real economy', *The Review of Financial Studies*, vol. 34, no. 11, pp. 5135-5148.

Gomes, M, and Chaibi, A 2014, ‘Volatility spillovers between oil prices and stock returns: A focus on frontier markets’, *Journal of Applied Business Research,* vol. 30, no. 2, pp. 509-526.

González, MT, and Novales, A 2009, ‘Are volatility indices in international stock markets forward looking?’ *RACSAM-Revista de la Real Academia de Ciencias Exactas, Fisicas y Naturales. Serie A. Matematicas,* vol. 103, pp. 339-352.

Goudarzi, H 2013, 'Volatility mean reversion and stock market efficiency ', *Asian Economic and Financial Review,* vol. 3, no. 12, pp. 1681-1692.

Goudarzi, H and Ramanarayanan, CS 2010, ‘Modeling and estimation of volatility in the Indian stock market’, *International Journal of Business and Management,* vol. 5, no. 2, pp. 85-98.

Granger, C 1969, ‘Investigating causal relations by econometric models and cross-spectral methods’, *Econometrica,* vol. 37, no. 3, pp. 424-438.

Granger, C 1981, ‘Some properties of time series data and their use in econometric model specification’, *Journal of Econometrics,* vol. 16, no. 1, pp. 121-30.

Granger, C and Hallman, J 1991, ‘Long memory series with attractors’, *Oxford Bulletin of Economics and Statistics*, vol. 53, no. 1, pp. 11-26.

Granger, C, Morgenstern, O, and Granger, C 1970, ‘Spectral analysis of New York stock market prices’, *Essays in Econometrics,* vol. 1, pp. 85-105.

Griffin, P and Sanvicente, A 1982, ‘Common stock returns and rating changes: A methodological comparison’, *The Journal of Finance*, vol. 37, no. 1, pp. 103-119.

Groenewold, N and Ariff, N 1998, ‘The effects of deregulation on share market efficiency in the Asia-Pacific’, *International Economic Journal*, vol. 12, no. 4, pp. 23-47.

Guhathakurta, K, Dash, SR and Maitra, D 2020, ‘Period specific volatility spillover based connectedness between oil and other commodity prices and their portfolio implications', *Energy Economics*, vol. 85, article no. 104566, viewed 3 June 2021, https://doi.org/10.1016/j.eneco.2019.104566

Gujarati, D, Porter, D 2009, *Basic econometrics (fifth ed)*, McGraw-Hill, NYC, USA.

Gulen, H, and Ion, M 2016, 'Policy uncertainty and corporate investment', *The Review of Financial Studies*, vol. 29, no. 3, pp. 523-564

Gulen, H, and Mayhew, S 2000, 'Stock index futures trading and volatility in international equity markets', *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, vol. *20*, no. 7, pp. 661-685.

Hacibedel, B and Van Bommel, J 2007, 'Do emerging markets benefit from index inclusion?', *Money Macro and Finance (MMF) Research Group Conference. University of Birmingham, Birmingham, 12-14 September 2007.*

Hafner, C, and Herwartz, H 2006, 'Volatility impulse responses for multivariate GARCH models: An exchange rate illustration', *Journal of International Money and Finance*, vol. 25, no.5, pp. 719-740.

Hair, JF, Hult, GTM, Ringle, C and Sarstedt, M 2014, *A primer on partial least squares structural equation modeling (PLS-SEM)*, Sage: Newbury Park, CA.

Hamao, Y, Masulis, R, and Ng, V 1990, 'Correlations in price changes and volatility across international stock markets', *The Review of Financial Studies*, vol. 3, no. 2, pp. 281-307.

Hamdi, B, Aloui, M, Alqahtani, F, and Tiwari, A 2019, 'Relationship between the oil price volatility and sectoral stock markets in oil-exporting economies: Evidence from wavelet nonlinear denoised based quantile and Granger-causality analysis', *Energy Economics*, vol. 80, pp. 536-552.

Hammoudeh, S Aleisa, E 2004, ‘Dynamic relationships among GCC stock markets and NYMEX oil futures’, *Contemporary Economic Policy,* vol. 22, no. 2, pp. 250-269.

Hammoudeh, S and Choi, K 2006, ‘Behavior of GCC stock markets and impacts of US oil and financial markets’, *Research in International Business and Finance,* vol. 20, no. 1, pp. 22-44.

Hammoudeh, S and Choi, K 2007, ‘Characteristics of permanent and transitory returns in oil-sensitive emerging stock markets: The case of GCC countries’, *Journal of International Financial Markets, Institutions and Money,* vol. 17, no. 3, pp. 231-245.

Hammoudeh, SM, Yuan, Y and McAleer, M 2009, ‘Shock and volatility spillovers among equity sectors of the Gulf Arab stock markets’, *The Quarterly Review of Economics and Finance,* vol. 49, no. 3, pp. 829-842.

Han, H 2015, ‘Asymptotic Properties of GARCH-X Processes’, *Journal of Financial Econometrics,* vol. 13, no. 1, pp. 188-221.

Hart, CE, Lence, SH, Hayes, DJ and Jin, N 2015, ‘Price mean reversion, seasonality, and options markets’ *American Journal of Agricultural Economics,* vol. 98, pp. 707-725.

Hasbullaha, ES, Rusyamanb, E, and Kartiwac, A 2020, ‘The GARCH model volatility of sharia stocks associated causality with market index’, *International Journal of Quantitative Research and Modeling,* vol. 1, no. 1, pp. 18-28.

Hassan, K, Hoque, A and Gasbarro, D 2019, ‘Separating BRIC using Islamic stocks and crude oil: Dynamic conditional correlation and volatility spillover analysis’, *Energy Economics,* vol. 80, pp. 950-969.

Hassan, K, Hoque, A, Wali, M, and Gasbarro, D 2020, ‘Islamic stocks, conventional stocks, and crude oil: directional volatility spillover analysis in BRICS’. *Energy Economics*, vol. 92, article no. 104985, viewed 17 August 2022, https://doi.org/10.1016/j.eneco.2020.104985.

Hayat, A, and Tahir, M 2021, ‘Natural resources volatility and economic growth: Evidence from the resource-rich region’ *Journal of Risk and Financial Management*, vol. 14, no. 2, article no. 84, viewed 15 May 2023, https://doi.org/10.3390/jrfm14020084

He, P, Sun, Y, Zhang, Y and Li, T 2020, ‘COVID–19’s Impact on Stock Prices Across Different Sectors - An Event Study Based on the Chinese Stock Market’, *Emerging Markets Finance and Trade*, vol. 56, no. 10, pp. 2198-2212.

Henry, PB 2000, ‘Stock market liberalization, economic reform, and emerging market equity prices’, *The Journal of Finance*, vol. 55, no. 2, pp. 529-564.

Ho, K-Y, Shi, Y and Zhang, Z 2020, ‘News and return volatility of Chinese bank stocks’, *International Review of Economics & Finance*, vol. 69, pp. 1095-1105.

Hoang, BT, and Mateus, C 2023, ‘How does liberalization affect emerging stock markets? Theories and empirical evidence’, *Journal of Economic Surveys*, vol. 0, pp. 1-22.

Hodoshima, J 2018, ‘Stock performance by utility indifference pricing and the Sharpe ratio’, *Quantitative Finance*, vol. 19, no. 2, pp. 327-338.

Hong, H and Kacperczyk, M 2009, ‘The price of sin: The effects of social norms on markets’, *Journal of Financial Economics*, vol. 93, no. 1, pp. 15-36.

Hong, Y 2001, ‘A test for volatility spillover with application to exchange rates’, *Journal of Econometrics*, vol. 103, no. 1-2, pp. 183-224.

Horváth, L, Kokoszka, P, and Rice, G 2014, ‘Testing stationarity of functional time series’, *Journal of Econometrics*, vol. 179, no. 1, pp. 66-82.

https://doi.org/10.3390/ijfs7040065.

Huang, X 2017, 'Value-at-risk under Lévy G.A.R.C.H. models: Evidence from global stock markets', *CFA Digest*, vol. 47, no. 6, pp. 30-53.

Hung, N 2018, 'Volatility behaviour of the foreign exchange rate and transmission among central and eastern European countries: Evidence from the EGARCH model', *Global Business Review*, vol. 22, no. 12, pp.1-21.

Hung, NT 2021,'Financial connectedness of GCC emerging stock markets', *Eurasian Economic Review*, vol. 11, no. 4, pp. 753-773.

Hussain, S, Murthy, KV and Singh, A 2019, 'Stock market volatility: A review of the empirical literature', *IUJ Journal of Management*, vol. 7, no. 1, article no. 07.01.15, viewed 19 May 2022, https://eoi.citefactor.org/10.11224/IUJ.07.01.15.

Huynh, LDT 2019, 'Spillover risks on cryptocurrency markets: A look from VAR-SVAR granger causality and student's-t copulas', Journal of Risk and Financial Management, vol. 12, no. 2, article no. 52, viewed 20 May 2023, https://doi.org/10.3390/jrfm12020052

IEA 2017, *World energy investment 2017*. Paris, France: IEA.

Iqbal, N, Manzoor, MS and Bhatti, MI 2021, 'Asymmetry and leverage with news impact curve perspective in Australian stock returns volatility during COVID-19', *Journal of Risk and Financial Management*, vol. 14, no. 7, pp. 314-329.

Iqbal, Z, and Mirakhor, A 2012, *An introduction to Islamic finance: Theory and practice* 2nd edn. Hoboken, NJ: John Wiley & Sons.

Issing, O 2000, 'The globalisation of financial markets', *European Central Bank Working Paper No. 12 September 2000*, viewed 27 September 2021, https://www.ecb.europa.eu/press/key/date/2000/html/sp000912_2.en.html.

Izadi, S and Hassan, MK 2018, ‘Portfolio and hedging effectiveness of financial assets of the G7 countries’, *Eurasian Economic Review*, vol. 8, no. 2, pp. 183-213.

Izadi, S and Hassan, MK 2018, ‘Portfolio and hedging effectiveness of financial assets of the G7 countries’, *Eurasian Economic Review*, vol. 8, pp. 183-213.

Izzeldin, M, Muradoğlu, YG, Pappas, V, and Sivaprasad, S 2021, ‘The impact of Covid-19 on G7 stock markets volatility: Evidence from a ST-HAR model’, *International Review of Financial Analysis*, vol. 74, article no. 101671, viewed 23 May 2023, https://doi.org/10.1016/j.irfa.2021.101671

Janani Sri, S, Kayal, P and Balasubramanian, G 2022, ‘Can equity be safe-haven for investment?', *Journal of Emerging Market Finance*, vol. 21, no. 1, pp. 32-63.

Janssen, G 2004, ‘Public information arrival and volatility persistence in financial markets’, *The European Journal of Finance*, vol. 10, no. 3, pp. 177-197.

Jarque, C, and Bera, A 1981, ‘Efficient tests for normality, homoscedasticity and serial independence of regression residuals: Monte Carlo evidence’, *Economics Letters*, vol. 7, no. 4, pp. 313-318.

Jayasuriya, S 2005, ‘Stock market liberalization and volatility in the presence of favorable market characteristics and institutions’, *Emerging Markets Review*, vol. 6, no. 2, pp. 170-191.

Jebabli, I, Kouaissah, N, and Arouri, M 2022, ‘Volatility spillovers between stock and energy markets during crises: A comparative assessment between the 2008 global financial crisis and the COVID-19 pandemic crisis’, *Finance Research Letters*, vol. 46, article no. 102363, viewed 24 May 2023, https://doi.org/10.1016/j.frl.2021.102363

Jebran, K 2018, ‘Volatility spillover between stock and foreign exchange market of China: Evidence from subprime Asian financial crisis’, *Journal of Asia Business Studies*, vol. 12, no. 2, pp. 220-232.

Jebran, K, Chen, S, Ullah, I, and Mirza, S 2017, ‘Does volatility spillover among stock markets varies from normal to turbulent periods? Evidence from emerging markets of Asia’, *The Journal of Finance and Data Science*, vol. 3, no.1-4, pp. 20-30.

Jentsch, C, and Rao, S 2015, ‘A test for second order stationarity of a multivariate time series’, *Journal of Econometrics*, vol. 185, no. 1, pp. 124-161.

John, A, Logubayom, AI and Nero, R 2019, ‘Half-life volatility measure of the returns of some cryptocurrencies', *Journal of Financial Risk Management*, vol. 8, no. 1, pp. 15-28.

Johnson, R, and Soenen, L 2002, ‘Asian economic integration and stock market comovement’, *Journal of Financial Research*, vol. 25, no.1, pp. 141-157.

Jouini, J 2013, ‘Return and volatility interaction between oil prices and stock markets in Saudi Arabia’, *Journal of Policy Modeling*, vol. 35, no. 6, pp. 1124-1144.

Jouini, J and Harrathi, N 2014, ‘Revisiting the shock and volatility transmissions among GCC stock and oil markets: A further investigation’, *Economic Modelling*, vol. 38, pp. 486-494.

Jung Park, Y, Kutan, AM and Ryu, D 2019, ‘The impacts of overseas market shocks on the CDS-option basis’, *The North American Journal of Economics and Finance*, vol. 47, pp. 622-636.

Kalyanaraman, L 2014, ‘Stock market volatility in Saudi Arabia: An application of univariate GARCH model’, *Asian Social Science*, vol. 10, no. 10, pp. 142.

Kambouroudis, DS 2016, ‘Modeling and forecasting stock market volatility in frontier markets: Evidence from four European and four African frontier markets’, *in Handbook of Frontier Markets* (eds), pp. 39-54.

Karali, B and Ramirez, OA 2014, ‘Macro determinants of volatility and volatility spillover in energy markets’, *Energy Economics*, vol. 46, pp. 413-421.

Karmakar, M and Shukla, GK 2016, ‘The effect of spillover on volatility forecasting: An empirical study in Indian stock market’, *Metamorphosis: A Journal of Management Research*, vol. 15, no. 1, pp. 20-30.

Karolyi, G A 2001, ‘Why Stock Return Volatility Really Matters’, *Institutional Investor Journals Series*, vol. (614), pp. 1-16.

Karunanayake, I, Valadkhani, A, and O'brien, M 2010, ‘Financial crises and international stock market volatility transmission’, *Australian Economic Papers*, vol. 49, no. 3, pp. 209-221.

Kearney, C and Lucey, B 2004, ‘International equity market integration: Theory, evidence and implications’, *International Review of Financial Analysis*, vol. 13, no. 5, pp. 571-583.

Kearney, C and Lucey, BM 2004, ‘International equity market integration: Theory, evidence and implications’, *International Review of Financial Analysis*, vol. 13, no. 5, pp. 571-583.

Kemp, J 2017, *COLUMN-volatility and cyclicality in oil prices - will this time be different.* London, UK: Reuters

Khalifa, AA, Hammoudeh, S and Otranto, E 2014, ‘Patterns of volatility transmissions within regime switching across GCC and global markets’, *International Review of Economics & Finance*, vol. 29, pp. 512-524.

Kim, B, Kim, H, and Lee, B 2015, 'Spillover effects of the US financial crisis on financial markets in emerging Asian countries', *International Review of Economics Finance,* vol. 39, no. C, pp. 192-210.

Kim, S, and Rogers, J 1995, 'International stock price spillovers and market liberalization: Evidence from Korea, Japan, and the United States', *Journal of Empirical Finance*, vol. 2, no. 2, pp. 117-133.

King, M, Sentana, E, and Wadhwani, S 1990, 'Volatility and links between national stock markets', *Econometrica,* vol. 62, no. 4, pp. 901-933

Kirchler, M and Huber, J 2007, 'Fat tails and volatility clustering in experimental asset markets', *Journal of Economic Dynamics and Control*, vol. 31, no. 6, pp. 1844-1874.

Kondoz, M, Bora, I, Kirikkaleli, D, and Athari, S 2019, 'Testing the volatility spillover between crude oil price and the U.S. stock market returns', *Management Science Letters,* vol. 9, no. 8, pp. 1221-1230.

Koumou, GB 2020, 'Diversification and portfolio theory: A review', *Financial Markets and Portfolio Management*, vol. 34, no. 3, pp. 267-312.

Koutmos, G, and Booth, G 1995, 'Asymmetric volatility transmission in international stock markets', *Journal of International Money and Finance,* vol. 14, no 6, pp. 747-762.

Kroner, K, and Ng, V 1998, 'Modeling asymmetric comovements of asset returns', *The Review of Financial Studies*, vol. 11, no. 4, pp. 817-844.

Kroner, K, and Sultan, J 1993, 'Time-varying distributions and dynamic hedging with foreign currency futures', *The Journal of Financial and Quantitative Analysis*, vol. 28, no. 4, pp. 535-551.

Kumar, D 2014, ‘Return and volatility transmission between gold and stock sectors: Application of portfolio management and hedging effectiveness’, *IIMB Management Review*, vol. 26, no. 1, pp. 5-16.

Kumar, KK and Mukhopadhyay, C 2007, ‘Volatility spillovers from the US to Indian stock market: A comparison of GARCH models’, *The IUP Journal of Financial Economics*, vol. V, no. 4, pp. 7-30.

Kumar, S, Moonhaque, M, and Sharma, P 2017, ‘Volatility spillovers across major emerging stock markets’, *Asia-Pacific Journal of Management Research and Innovation*, vol. 13, no 1-2, pp. 13-33.

Kwiatkowski, D, Phillips, P, Schmidt, P, and Shin, Y 1992, ‘Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?’, *Journal of Econometrics*, vol. 54, no. 1-3, pp. 159-178.

Lamoureux, CG, and Lastrapes, WD 1990, ‘Persistence in variance, structural change, and the GARCH model’ *Journal of Business & Economic Statistics*, vol. 8, no. 2, pp. 225-234.

Lawler, A 2017, *OPEC, Russia agree oil cut extension to end of 2018*. London, UK: Reuters.

Ledoit, O, Wolf, M 2003, ‘Improved estimation of the covariance matrix of stock returns with an application to portfolio selection’. *Journal of Empirical Finance*, vol.10, no. 5, pp. 603-621.

Lee, SJ 2009, ‘Volatility spillover among stock markets in six Asian countries and the United States’, *SSRN Electronic Journal*, article no. 838391, viewed 11 November 2021, http://dx.doi.org/10.2139/ssrn.838391.

Lee, TH 1994, 'Spread and volatility in spot and forward exchange rates', *Journal of International Money and Finance*, vol. 13, no. 3, pp. 375-383.

Levine, D, Stephan, D, Krehbiel, T, Berenson, M 2008, *Statistics for Managers Using Microsoft Excel*, Pearson Prentice-Hall, New Jersey, USA.

Levine, R 2002, 'International financial liberalization and economic growth', *Review of International Economics*, vol. 9, no. 4, pp. 684-698.

Levine, R and Zervos, S 1998, 'Capital control liberalization and stock market development', *World Development*, vol. 26, no. 7, pp. 1169-1183.

Li, MC, Lai, CC & Xiao, L 2021, 'Did COVID-19 increase equity market risk exposure? Evidence from China, the UK, and the US', *Applied Economics Letters*, vol. 29, no. 6, pp. 567-571.

Li, Y, Liu, J, Wang, H, and Wang, P 2020, 'Stock market liberalization, foreign institutional investors, and informational efficiency of stock prices', *International Journal Of Finance And Economics*, vol. 26, no. 4, pp. 5451-5471.

Liao, L, Liu, B and Wang, H 2011, 'Information discovery in share lockups: Evidence from the split-share structure reform in China', *Financial Management*, vol. 40, no. 4, pp. 1001-1027.

Liao, L, Pan, Y, and Yao, D 2022, 'Capital market liberalisation and voluntary corporate social responsibility disclosure: Evidence from a quasi-natural experiment in China', *Accounting & Finance*, article no. 12988, viewed 13 May 2023, https://doi.org/10.1111/acfi.12988

Lin, W, Engle, R, and Ito, T 1991, 'Do bulls and bears move across borders? International transmission of stock returns and volatility as the world turns', *National Bureau of Economic Research Working Paper No. 3911*, viewed 19 January 2021, http://dx.doi.org/10.3386/w3911.

Liu, J 2007, ‘Portfolio selection in stochastic environments’, *The Review of Financial Studies*, vol. 20, no. 1, pp. 1-39.

Liu, Y, Lu, H and Veenstra, K 2014, ‘Is sin always a sin? The interaction effect of social norms and financial incentives on market participants’ behavior’, *Accounting, Organizations and Society*, vol. 39, no. 4, pp. 289-307.

Lockwood, LJ and Linn, SC 1990, ‘An examination of stock market return volatility during overnight and intraday periods, 1964–1989’, *The Journal of Finance*, vol. 45, no. 2, pp. 591-601.

Maddala, G 2001, *Introduction to econometrics*, NYC, USA: Wiley & Sons Publishers.

Maddala, G, and Wu, S 1999, ‘A comparative study of unit root tests with panel data and a new simple test’, *Oxford Bulletin of Economics and statistics*, vol. 61, no. 1, pp. 631-652.

Maitra, D, and Dawar, V 2018, ‘Return and volatility spillover among commodity futures, stock market and exchange rate: Evidence from India’, *Global Business Review*, vol. 20, no. 1, pp. 214-237.

Malik, F, Ewing, BT and Payne, JE 2005, ‘Measuring volatility persistence in the presence of sudden changes in the variance of Canadian stock returns’, *The Canadian Journal of Economics*, vol. 38, no. 3, pp. 1037-1056.

Mallikarjunappa, T and Afsal, EM 2008, ‘The impact of serivatives on stock market volatility: A study of the Nifty index’, *Asian Academy of Management Journal of Accounting & Finance*, vol. 4, no. 2, pp. 43-65.

Mandelbrot, B 1963, ‘The variation of certain speculative prices’, *Journal of Business* vol. 36, pp. 394-419.

Markowitz, H 1952, ‘Portfolio Selection’, *The Journal of Finance*, vol. 7, no. 1, pp. 77-91.

Marshall, BR, Nguyen, NH and Visaltanachoti, N 2015, ‘Frontier market transaction costs and diversification’, *Journal of Financial Markets*, vol. 24, pp. 1-24.

Martens, M, and Poon, S 2001, ‘Returns synchronization and daily correlation dynamics between international stock markets’, *Journal of Banking & Finance*, vol. 25, no. 10, pp. 1805-1827.

McAleer, M 2014, ‘Asymmetry and Leverage in Conditional Volatility Models’, *Econometrics*, vol. 2, no. 3, pp. 145-150.

McAleer, M and Hafner, C 2014, ‘A one line derivation of EGARCH’, *Econometrics*, vol. 2, no. 2, pp. 92-97.

McAleer, M, Hoti, S and Chan, F 2009, ‘Structure and asymptotic theory for multivariate asymmetric conditional volatility’, *Econometric Reviews*, vol. 28, no. 5, pp. 422-440.

Medhioub, I and Chaffai, M 2019, ‘Islamic finance and herding behavior theory: A sectoral analysis for Gulf Islamic stock market’, *International Journal of Financial Studies*, vol. 7, no. 4, article no. 7040065, viewed 22 October 2021,

Meloni, C, Pranzo, M, and Samà, M 2022, ‘Evaluation of VaR and CVaR for the makespan in interval valued blocking job shops’, *International Journal of Production Economics*, vol. 247, article no. 108455, viewed 22 October 2022, https://doi.org/10.1016/j.ijpe.2022.108455.

Mendes, B and Martins, R 2018, ‘Determinants of stock market classifications’, *Applied Economics Letters*, vol. 25, no. 17, pp. 1244-1249.

Mensi, W, Hammoudeh, S, Al-Jarrah, I, Al-Yahyaee, K, and Kang, S 2021, ‘Risk spillovers and hedging effectiveness between major commodities, and Islamic and conventional GCC banks’ *Journal of International Financial Markets, Institutions & Money*, vol. 60, pp. 68-88.

Meriç, İ, Ding, J, and Meriç, G 2016, ‘Global portfolio diversification with emerging stock markets’, *Emerging Markets Journal,* vol. 6, no. 1, pp. 59-62.

Mert, URAL 2016, ‘The impact of the global financial crisis on crude oil price volatility’, *Journal of Management and Economics Research*, vol. 14, no. 2, pp. 64-76.

Mhmoud, A and Dawalbait, F 2015, ‘Estimating and forcasting stock market volatility using GRACH models: Empirical evidence from Saudi Arabia’, *International Journal of Engineering Research & Technology,* vol. 4, no. 2, pp. 1-8.

Mikhaylov, A 2018, ‘Volatility spillover effect between stock and exchange rate in oil exporting countries’, *International Journal of Energy Economics and Policy,* vol. 8, no. 3, pp. 321-326.

Mimouni, K and Charfeddine, L 2016, ‘Do oil producing countries offer international diversification benefits? Evidence from GCC countries’, *Economic Modelling,* vol. 57, pp. 263-280.

Mohanty, SK and Nandha, M 2011, ‘Oil shocks and equity returns: an empirical analysis of the US transportation sector’, *Review of Pacific Basin Financial Markets and Policies,* vol. 14, no. 01, pp. 101-128.

Mollah, S and Mobarek, A 2016, *Global stock market integration: Co-movement, crises, and efficiency in developed and emerging markets*. New York: Springer.

MSCI 2018, *Results of MSCI 2018 market classification review*. New York: MSCI Inc.

Myers, R 1991, ‘Estimating time-varying optimal hedge ratios on futures markets’, *The Journal of Futures Markets,* vol. 11, no. 1, pp. 39-53.

Naifar, N 2016, ‘Modeling dependence structure between stock market volatility and sukuk yields: A nonlinear study in the case of Saudi Arabia’, *Borsa Istanbul Review,* vol. 16, no. 3, pp. 157-66.

Naimy, V, Haddad, O, Fernandez-Aviles, G and El Khoury, R 2021, ‘The predictive capacity of GARCH-type models in measuring the volatility of crypto and world currencies’, *PLoS One*, vol. 16, no. 1, p. article no. 0245904, viewed 12 June 2022, https://doi.org/10.1371/journal.pone.0245904.

Nasar, S 1991, ‘For Fed, a new set of tea leaves’, *New York Times*, vol. 140, no. 48652, p.1.

Natarajan, VK, Singh, ARR and Priya, NC 2014, ‘Examining mean-volatility spillovers across national stock markets’, *Journal of Economics Finance and Administrative Science*, vol. 19, no. 36, pp. 55-62.

Neaime, S 2006, ‘Volatilities in emerging MENA stock markets’, *Thunderbird international business review*, vol. 48, no. 4, pp. 455-484.

Neaime, S 2015, ‘Are emerging M.E.N.A. stock markets mean reverting? A Monte Carlo simulation’, *Finance Research Letters*, vol. 13, pp. 74-80.

Nelson, D 1991, ‘Conditional heteroscedasticity in assets returns: A new approach’, *Econometrica*, vol. 59, no. 2, pp. 347-370.

Ng, A 2000, ‘Volatility spillover effects from Japan and the US to the Pacific–Basin’, *Journal of International Money and Finance,* vol. 19, no. 2, pp. 207-233.

Ngare, E, Nyamongo, E, and Misati, R 2014, ‘Stock market development and economic growth in Africa’, *Journal of Economics and Business*, vol. 74, pp. 24-39.

Ngene, G, Carley, H, and Hassan, MK 2014, ‘Persistence of volatility of sovereign credit risk in presence of structural breaks’, *Journal of Derivatives & Hedge Funds*, vol. 20, no. 1, pp. 10-27.

Nieto, B, and Rubio, G 2022, ‘The Effects of the COVID-19 Crisis on Risk Factors and Option-Implied Expected Market Risk Premia: An International Perspective’, *Journal of Risk and Financial Management*, vol. 15, no. 1.

Nikkinen, J, Omran, M, Sahlström, P, and Äijö, J 2006, 'Global stock market reactions to scheduled U.S. macroeconomic news announcements', *Global Finance Journal*, vol. 17, no. 1, pp. 92-104.

Ning, C, Xu, D and Wirjanto, TS 2015, 'Is volatility clustering of asset returns asymmetric?', *Journal of Banking & Finance*, vol. 52, pp. 62-76.

Norden, L and Weber, M 2004, 'Informational efficiency of credit default swap and stock markets: The impact of credit rating announcements', *Journal of Banking & Finance*, vol. 28, pp. 2813-2843.

Nugroho, DB, Kurniawati, D, Panjaitan, LP, Kholil, Z, Susanto, B and Sasongko, LR 2019, 'Empirical performance of GARCH, GARCH-M, GJRGARCH and log-GARCH models for returns volatility', *Journal of Physics: Conference Series*, vol. 1307, no. 1, p. article no. 012003, viewed 19 November 2021, https://doi.org/10.1088/1742-6596/1307/1/012003.

O'Neill, TJ, Penm, J, and Terrell, RD 2008, 'The role of higher oil prices: A case of major developed countries', *Research in Finance*, vol. 24, pp. 287-299.

Olowe, RA 2009, 'Modelling Naira/Dollar exchange rate volatility: Application of GARCH And assymetric models', *International Review of Business Research Papers*, vol. 5, no. 3, pp. 377-398.

Olson, E, Vivian, A, Wohar, M 2014, 'The relationship between energy and equity markets: evidence from volatility impulse response functions', *The Journal of Energy Economics*, vol. 43, pp. 297-305.

Olson, E, Vivian, A, Wohar, M 2017, 'Do commodities make effective hedges for equity investors?', *The Journal of Research in International Business and Finance,* vol. 42, pp. 1274-1288.

Osman, AM, Ahmed, AO, Eltahir, MN, Mohamed, AS, Shidwan, OS, and Ghada, M 2019, 'Investigating the causes of inflation in Saudi Arabia: An application of autoregressive distributed lag (ARDL) model', *International Journal of Applied Engineering Research*, vol. 14, no. 21, pp. 3980-3986.

Panton, D, Lessig, V, and Joy, O 1976, 'Comovement of international equity markets: A taxonomic approach', *The Journal of Financial and Quantitative Analysis*, vol. 11, no. 3, pp. 415.

Paparoditis, E, and Politis, D 2018, 'The asymptotic size and power of the augmented dickey-fuller test for a unit root', *Econometric Reviews,* vol. 37, no.1, pp. 955-973.

Park, D, Park, J and Ryu, D 2020, 'Volatility spillovers between equity and green bond markets', *Sustainability,* vol. 12, no. 9. pp. 1-12.

Park, T, Switzer, L 1995, 'Time-varying distributions and the optimal hedge ratios for stock index futures' *The Journal of Applied Financial Economics*, vol. 5, no. 3, pp. 131-137.

Park, YJ, Kutan, AM and Ryu, D 2019, 'The impacts of overseas market shocks on the CDS-option basis', *The North American Journal of Economics and Finance,* vol. 47, pp. 622-636.

Parkinson, M 1980, 'The extreme value method for estimating the variance of the rate of return', *The Journal of Business*, vol. 53, no. 1, pp. 61-65.

Pati, PC, and Rajib, P 2011, 'Intraday return dynamics and volatility spillovers between NSE S&P CNX Nifty stock index and stock index futures', *Applied Economics Letters*, vol. 18, no. 6, pp. 567-574.

Phillips, P, Perron, P 1988, 'Testing for a Unit Root in Time Series Regression', *Biometrika,* vol. 75, no. 2, pp. 335-346.

Poon, S, and Granger, C 2003, ‘Forecasting volatility in financial markets: A review’, *Journal of Economic Literature*, vol. 41, no. 2, pp. 478-539.

Poterba, JM and Summers, LH 1984, *The persistence of volatility and stock market fluctuations*, National Bureau of Economic Research, Cambridge, MA.

Poterba, JM and Summers, LH 1986, ‘The persistence of volatility and stock market fluctuations’, *The American Economic Review*, vol. 76, no. 5, pp. 1142-1151.

Premaratne, G, and Balasubramanyan, L 2003, ‘Stock market volatility: Examining North America, Europe and Asia’, *National University of Singapore Economics Working PaperNo 375380*, viewed 18 June 2021, http://dx.doi.org/10.2139/ssrn.375380.

Press, W, Teukolsky, SA, Vetterling, WT and Flannery, BP 2007, *Numerical recipes, The Art of Scientific Computing (3rd ed.).* Cambridge: Cambridge University Press, UK.

Prokopczuk, M, and Simen, CW 2014, ‘The importance of the volatility risk premium for volatility forecasting’, *Journal of Banking & Finance*, vol. 40, pp. 303-320.

Pugel, TA 2016, *International economics (6th ed.).* NYC, NY: McGraw Hill.

Rajhans, R and Jain, A 2015, ‘Volatility spillover in foreign exchange markets’, *Paradigm*, vol. 19, no. 2, pp.137-151.

Rajput, OSK, Memon, AA, Siyal, TA, and Bajaj, NK 2023, ‘Volatility spillovers among Islamic countries and geopolitical risk’, *Journal of Islamic Accounting and Business Research*, Vol. ahead-of-print, viewed 22 May 2023, https://doi.org/10.1108/JIABR-07-2022-0173.

Rejeb, AB, Boughrara, A 2013, ‘Financial liberalization and stock markets efficiency: New evidence from emerging economies’, *Emerging Markets Review*, vol. 17, no. C, pp. 186-208.

Ribeiro, PP, Cermeño, R and Curto, JD 2017, ‘Sovereign bond markets and financial volatility dynamics: Panel-G.A.R.C.H. evidence for six euro area countries’, *Finance Research Letters*, vol. 21, pp. 107-114.

Richards, A 1996, ‘Comovements in national stock market returns: Evidence of predictability but not cointegration’, *IMF Working Paper No. 1996/028*, vol. 96, no. 28, pp. 1-30.

Rigobón, R 2016, ‘Contagion, spillover and interdependence’, *Economía*, vol. 19, no. 2, pp. 69-100.

Roll, R 1977, ‘A critique of the asset pricing theory's tests Part I: On past and potential testability of the theory’, *Journal of financial economics*, vol. 4, no. 2, pp. 129-176.

Rothe, C and Sibbertsen, P 2006, ‘Phillips-Perron-type unit root tests in the nonlinear ESTAR framework’, *Allgemeines Statistisches Archiv*, vol. 90, pp. 439-456.

Rydberg, TH 2000, ‘Realistic Statistical Modelling of Financial Data’, *International Statistical Review*, vol. 68, no. 3, pp. 233-58.

S&P Dow Jones Indices 2018, *S&P Dow Jones Indices’ 2018 country classification consultation*. New York: S&P Dow Jones Indices.

Saiti, B and Mansur, M 2016, ‘The co-movement of selective conventional and Islamic stock indices: Is there any impact on shariah compliant equity investment in China?’, *International Journal of Economics and Financial* Issues, vol. 6, no. 4, pp. 1895-1905.

Sakti, MRP, Masih, M, Saiti, B and Tareq, MA 2018, ‘Unveiling the diversification benefits of Islamic equities and commodities: Evidence from multivariate-GARCH and continuous wavelet analysis’, *Managerial Finance*, vol. 44, pp. 830-850.

Saleem, A, Bárczi, J, Sági, J 2021, ‘COVID-19 and Islamic stock index: Evidence of market behavior and volatility persistence’, *Journal of Risk and Financial Management*, vol. 14, no. 8, article no. 389, viewed 24 October 2022, https://doi.org/10.3390/jrfm14080389.

Saleem, K 2009, ‘International linkage of the Russian market and the Russian financial crisis: A multivariate GARCH analysis’, *Research in International Business and Finance,* vol. 23, no. 3, pp. 243-256.

Salisu, AA, Ogbonna, AE, and Adediran, I 2021, ‘Stock-induced Google trends and the predictability of sectoral stock returns’, *Journal of Forecasting*, vol. 40, no. 2, pp. 327-345.

Sanford, AD 2011, ‘Granger causality in volatility between Australian equity and debt markets: A Bayesian analysis’, *Corporate Ownership & Control,* vol. 9, no. 1, pp. 587-596.

Sarwar, G 2012, ‘Is VIX an investor fear gauge in BRIC equity markets?’, *Journal of Multinational Financial Management,* vol. 22, no. 3, pp. 55-65.

Schneider, P, Wagner, C and Zechner, J 2020, ‘Low-Risk Anomalies?’, *The Journal of Finance*, vol. 75, no. 5, pp. 2673-718.

Segal, G, Shaliastovich, I, and Yaron, A 2015, ‘Good and bad uncertainty: Macroeconomic and financial market implications’, *Journal of Financial Economics*, vol. 117, no. 2, pp. 369-397.

Shafqat, A 2017, ‘Mean and volatility spillover effect from currency market to equity market’, Master of Science in Management Sciences (Finance), Capital University of Science and Technology, Islamabad.

Shahzad, SJH, Mensi, W, Hammoudeh, S, Rehman, MU and Al-Yahyaee, KH 2018, ‘Extreme dependence and risk spillovers between oil and Islamic stock markets’, *Emerging Markets Review*, vol. 34, pp. 42-63.

Sharpe, W 1966, ‘Mutual fund performance’, *Journal of Business,* , vol. 39, no. 1, pp. 119-138.

Shrestha, MB and Bhatta, GR 2018, ‘Selecting appropriate methodological framework for time series data analysis’, *The Journal of Finance and Data Science,* vol. 4, no. 2, pp. 71-89.

Simons, K 2000, ‘The use of value at risk by institutional investors’, *New England Economic Review*, vol. , no. Nov, pp. 21-30.

Singh, V and Roca, ED 2021, ‘Weathering financial crisis in China: The role of global market integration’, *Applied Economics*, vol. 53, no. 15, pp. 1756-1776.

Singhal, S 2016, *Hedge Fund Performance – Is Sharpe Ratio an Ideal Measure?*, Risk Advisors Inc., viewed 17 March 2022, <https://riskadvisorsinc.com/hedge-fund-performance-sharpe-ratio-ideal-measure>.

Singhal, S and Ghosh, S 2016, ‘Returns and volatility linkages between international crude oil price, metal and other stock indices in India: Evidence from VAR-DCC-GARCH models’, *Resources Policy*, vol. 50, pp. 276-288.

Slim, S, Koubaa, Y, and BenSaïda, A 2017, ‘Value-at-risk under Lévy G.A.R.C.H. models: Evidence from global stock markets’, *Journal of International Financial Markets, Institutions and Money*, vol. 46, pp. 30-53.

Solnik, B 1974, ‘Why not diversify internationally rather than domestically?’ *Financial Analysts Journal*, vol. 30, no. 4, pp. 48-54.

Spyridisa, T, Sevicb, Z and Theriouc, N 2010, ‘The long-run relationship between stock indices and economic factors in the ASE: An empirical study between 1989 and 2006’, *International Journal Of Business*, vol. 15, no. 4, pp. 425-443.

Suryadi, S, Endri, E and Yasid, M 2021, ‘Risk and return of Islamic and conventional indices on the Indonesia stock exchange’, *Journal of Asian Finance, Economics and Business*, vol. 8, no. 3, pp. 23-30.

Susmel, R, and Engle, R 1994, ‘Hourly volatility spillovers between international equity markets’, *Journal of International Money and Finance*, vol. 13, no. 1, pp. 3-25.

Tadawul 2015, *Annual report 2014*. Riyadh: Tadawul.

Tadawul 2018, *Annual report 2017*. Riyadh: Tadawul.

Tanin, T, Hasanov, A, Shaiban, M, and Brooks, R 2022, ‘Risk transmission from the oil market to Islamic and conventional banks in oil-exporting and oil-importing countries’, *Energy Economics*, vol. 115, article no. 106389, viewed 17 June 2022, https://doi.org/10.1016/j.eneco.2022.106389.

Tanizaki, H, and Hamori, S 2008, ‘Volatility transmission between Japan, UK and USA in daily stock returns’, *Empirical Economics*, vol.36, no. 1, pp. 27-54.

Tanty, G and Patjoshi, PK 2016, ‘Study on Stock Market Volatility Pattern of BSE and NSE in India’, *Asian Journal of Management*, vol. 7, no. 3, pp. 193-200.

The Strategist 2017, *Why are oil prices so volatile.* NYC, US: The Strategist.

Tien, HT, and Hung, NT 2022, ‘Volatility spillover effects between oil and GCC stock markets: a wavelet-based asymmetric dynamic conditional correlation approach’, *International Journal of Islamic and Middle Eastern Finance and Management*, vol. 15, no. 6, pp. 1127-1149.

Toyoshima, Y 2018, ‘Testing for causality-in-mean and Variance between the UK housing and stock markets’ *Journal of Risk and Financial Management,* vol. 11, no. 2, pp. 21.

Treynor, J 1965, ‘How to rate management of investment funds’, *Harvard Business Review*, vol. 41, pp. 63-75.

Trypsteen, S 2017, ‘The growth-volatility nexus: New evidence from an augmented G.A.R.C.H.-M model’, *Economic Modelling*, vol. 63, pp. 15-25.

Tsay, RS 2005, *Analysis of financial time series*, Wiley, New Jersey: USA.

Tse, Y, and Tsui, A 2002, ‘A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations’, *Journal of Business & Economic Statistics*, vol. 20, no. 3, pp. 351-362.

Tseng, JJ and Li, S P 2011, ‘Asset returns and volatility clustering in financial time series’, *Physica A: Statistical Mechanics and its Applications*, vol. 390, no. 7, pp. 1300-1314.

Uludag, K, and Khurshid, M 2019,’Volatility spillover from the Chinese stock market to E7 and G7 stock markets’, *Journal of Economic Studies*, vol. 46, no. 1, pp. 90-105.

Valenti, D, Fazio, G, and Spagnolo, B 2018, ‘The stabilizing effect of volatility in financial markets’, *Physical Review E,* vol. 97, no. 6, article no. 062307, viewed 17 May 2023, https://doi.org/10.1103/PhysRevE.97.062307

Valickova, P, Havranek, T, and Horvath, R 2015, ‘Financial development and economic growth: A meta-analysis’, *Journal of Economic Surveys*, vol. 29, no. 3, pp. 506-526.

Vo, X 2015, ‘Foreign ownership and stock return volatility: Evidence from Vietnam’, *Journal of Multinational Financial Management*, vol. 30, pp. 101-109.

Wang, J and Yang, M 2018, ‘Conditional volatility persistence’, *SSRN Paper No. 3080693*, viewed 11 May 2021, http://dx.doi.org/10.2139/ssrn.3080693

Wang, J, Zhang, D, and Zhang, J 2015, ‘Mean reversion in stock prices of seven Asian stock markets: Unit root test and stationary test with Fourier functions’ *International Review of Economics & Finance*, vol. 37, pp. 157-164.

Wang, Y, Pan, Z, Wu, C 2018. ‘Volatility spillover from the US to international stock markets: A heterogeneous volatility spillover GARCH model’ *Journal of Forecasting*, vol. 37, no. 3, pp. 385-400.

Weber, E, and Zhang, Y 2012, ‘Common influences, spillover and integration in Chinese stock markets’, *Journal of Empirical Finance*, vol. 19, no. 3, pp. 382-394.

Wegener, C, Kruse, R and Basse, T 2018, ‘The walking debt crisis’, *Journal of Economic Behaviour & Organization*, vol. 157, pp. 382-402.

Westfall, P 2014, ‘Kurtosis as peakedness, 1905 – 2014’, *RIP The American Statistician*, vol. 68, no. 3, pp. 191–195.

Wu, G 2001, ‘The determinants of asymmetric volatility’, Review of Financial Studies, vol. 14, no. 3, pp. 837-859.

Wyplosz, C 2001, ‘How risky is financial liberalizationin the developing countries?’, *CEPR Discussion Papers No. 2724*, viewed 7 April 2021, https://cepr.org/publications/dp2724.

Xiao, L, and Dhesi, G 2010, ‘Dynamic Linkages between the European and US Stock Markets’, *2010 Third International Conference on Business Intelligence and Financial Engineering. Hong Kong, China*, 13-15 Aug 2010.

Xiong, Z, and Han, L 2015, ‘Volatility spillover effect between financial markets: evidence since the reform of the RMB exchange rate mechanism’, *Financial Innovation*, vol. 1, no. 1, pp.1-12, Xuan Vinh, V and Ellis, C 2018, ‘International financial integration: Stock return linkages and volatility transmission between Vietnam and advanced countries’, *Emerging Markets Review*, vol. 36, no. C, pp. 19-27.

Yang, J, Kolari, J, and Sutanto, P 2004, ‘On the stability of long-run relationships between emerging and US stock markets’, *Journal of Multinational Financial Management*, vol. 14, no. 3, pp. 233-248.

Yang, YL and Chang, CL 2008, ‘A double-threshold GARCH model of stock market and currency shocks on stock returns’, *Mathematics and Computers in Simulation*, vol. 79, no. 3, pp. 458-474.

Yanikkaya, H 2003, ‘Trade openness and economic growth: A cross country empirical investigation’, *Journal of Development Economics*, vol. 72, no. 1, pp. 57-89.

Yeasin, M, Singh, KN, Lama, A and Paul, RK 2020, ‘Modelling volatility influenced by exogenous factorsusing an improved GARCH-X model’, *Journal Of The Indian Society Of Agricultural Statistics*, vol. 74, no. 3, pp. 209-216.

Yilmaz, K 2010, ‘Return and volatility spillovers among the East Asian equity markets’, *Journal of Asian Economics*, vol. 21, no. 3, pp. 304-13.

Yousaf, I, Beljid, M, Chaibi, A, and Ajlouni, AA 2022, ‘Do volatility spillover and hedging among GCC stock markets and global factors vary from normal to turbulent periods? Evidence from the global financial crisis and Covid-19 pandemic crisis’, *Pacific-Basin Finance Journal*, vol. 73, article no. 101764., viewed 10 May 2023, https://doi.org/10.1016/j.pacfin.2022.101764

Zakoian, J 1994, ‘Threshold heteroskedastic models’, *Journal of Economic Dynamics & Control*, vol. 18, no. 5, pp. 931-955.

Zhou, X, Zhang, W, and Zhang, J 2012, 'Volatility spillovers between the Chinese and world equity markets', *Pacific-Basin Finance Journal,* vol. 20, no. 2, pp. 247-270.

Zolfaghari, M, Ghoddusi, H, and Faghihian, F 2020, 'Volatility spillovers for energy prices: A diagonal BEKK approach'. *Energy Economics*, vol. 92, article no. 104965, viewed 18 April 2022, https://doi.org/10.1016/j.eneco.2020.104965.